Analysis and Design of Individual Information Systems to Support Health Behavior Change

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“Behavior is the end result of a prevailing story in one's mind:
change the story and the behavior will change.”

Dr. Jacinta Mpalyenkana

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Abstract

As a wide-ranging socio-technical transformation, the digitalization has significantly influenced the world, bringing opportunities and challenges to our lives. Despite numerous benefits like the possibility to stay connected with people around the world, the increasing dispersion and use of digital technologies and media (DTM) pose risks to individuals' well-being and health. Rising demands emerging from the digital world have been linked to digital stress, that is, stress directly or indirectly resulting from DTM (Ayyagari et al. 2011; Ragu-Nathan et al. 2008; Tarafdar et al. 2019; Weil and Rosen 1997), potentially intensifying individuals' overall exposure to stress. Individuals experiencing this adverse consequence of digitalization are at elevated risk of developing severe mental health impairments (Alhassan et al. 2018; Haidt and Allen 2020; Scott et al. 2017), which is why various scholars emphasize that research should place a stronger focus on analyzing and shaping the role of the individual in a digital world, pursuing instrumental as well as humanistic objectives (Ameen et al. 2021; Baskerville 2011b).

Information Systems (IS) research has long placed emphasis on the use of information and communication technology (ICT) in organizations, viewing an information system as the socio-technical system that emerges from individuals' interaction with DTM in organizations. However, socio-technical information systems, as the essence of the IS discipline (Lee 2004; Sarker et al. 2019), are also present in different social contexts from private life. Acknowledging the increasing private use of DTM, such as smartphones and social networks, IS scholars have recently intensified their efforts to understand the human factor of IS (Avison and Fitzgerald 1991; Turel et al. 2021). A framework recently proposed by Matt et al. (2019) suggests three research angles: analyzing individuals' behavior associated with their DTM use, analyzing what consequences arise from their DTM use behavior, and designing new technologies that promote positive or mitigate negative effects of individuals' DTM use. Various recent studies suggest that individuals' behavior seems to be an important lever influencing the outcomes of their DTM use (Salo et al. 2017; Salo et al. 2020; Weinstein et al. 2016).

Therefore, this dissertation aims to contribute to IS research targeting the facilitation of a healthy DTM use behavior. It explores the use behavior, consequences, and design of DTM for individuals' use with the objective to deliver humanistic value by increasing individuals' health through supporting a behavior change related to their DTM use. The dissertation combines behavioral science and design science perspectives and applies pluralistic methodological approaches from qualitative (e.g., interviews, prototyping) and quantitative research (e.g., survey research, field studies), including mixed-methods approaches mixing both. Following the framework from Matt et al. (2019), the dissertation takes three perspectives therein: analyzing individuals' behavior, analyzing individuals' responses to consequences of DTM use, and designing information systems assisting DTM users.

First, the dissertation presents new descriptive knowledge on individuals' behavior related to their use of DTM. Specifically, it investigates how individuals behave when interacting with DTM, why they behave the way they do, and how their behavior can be influenced. Today, a variety of digital workplace technologies offer employees different ways of pursuing their goals or performing their tasks (Köffer 2015). As a result, individuals exhibit different behaviors when interacting with these technologies. The dissertation analyzes what interactional roles DTM users can take at the digital workplace and what may influence their behavior. It uses a mixed-methods approach and combines a quantitative study building on trace data from a popular digital workplace suite and qualitative interviews with users of this digital workplace suite. The empirical analysis yields eight user roles that advance the understanding of users' behavior at the digital workplace and first insights into what factors may influence this behavior. A second study adds another perspective and investigates how habitual behavior can be changed by means of DTM design elements. Real-time feedback has been discussed as a promising way to do so (Schibuola et al. 2016; Weinmann et al. 2016). In a field experiment, employees working at the digital workplace are provided with an external display that presents real-time feedback on their office's indoor environmental quality. The experiment examines if and to what extent the feedback influences their ventilation behavior to understand the effect of feedback as a means of influencing individuals' behavior. The results suggest that real-time feedback can effectively alter individuals' behavior, yet the feedback's effectiveness reduces over time, possibly as a result of habituation to the feedback.

Second, the dissertation presents new descriptive and prescriptive knowledge on individuals' ways to mitigate adverse consequences arising from the digitalization of individuals. A frequently discussed consequence that digitalization has on individuals is digital stress. Although research efforts strive to determine what measures individuals can take to effectively cope with digital stress (Salo et al. 2017; Salo et al. 2020; Weinert 2018), further understanding

of individuals' coping behavior is needed (Weinert 2018). A group at high risk of suffering from the adverse effects of digital stress is adolescents because they grow up using DTM daily and are still developing their identity, acquiring mental strength, and adopting essential social skills. To facilitate a healthy DTM use, the dissertation explores what strategies adolescents use to cope with the demands of their DTM use. Combining a qualitative and a quantitative study, it presents 30 coping responses used by adolescents, develops five factors underlying adolescents' activation of coping responses, and identifies gender- and age-related differences in their coping behavior.

Third, the dissertation presents new prescriptive knowledge on the design of individual information systems supporting individuals in understanding and mitigating their perceived stress. Facilitated by the sensing capabilities of modern mobile devices, it explores the design and development of mobile systems that assess stress and support individuals in coping with stress by initiating a change of stress-related behavior. Since there is currently limited understanding of how to develop such systems, this dissertation explores various facets of their design and development. As a first step, it presents the development of a prototype aiming for life-integrated stress assessment, that is, the mobile sensor-based assessment of an individual's stress without interfering with their daily routines. Data collected with the prototype yields a stress model relating sensor data to individuals' perception of stress. To deliver a more generalized perspective on mobile stress assessment, the dissertation further presents a literature- and experience-based design theory comprising a design blueprint, design requirements, design principles, design features, and a discussion of potentially required trade-offs. Mobile stress assessment may be used for the development of mobile coping assistants. Aiming to assist individuals in effectively coping with stress and preventing future stress, a mobile coping assistant should recommend adequate coping strategies to the stressed individual in real-time or execute targeted actions within a defined scope of action automatically. While the implementation of a mobile coping assistant is yet up to future research, the dissertation presents an abstract design and algorithm for selecting appropriate coping strategies.

To sum up, this dissertation contributes new knowledge on the digitalization of individuals to the IS knowledge bases, expanding both descriptive and prescriptive knowledge. Through the combination of diverse methodological approaches, it delivers knowledge on individuals' behavior when using DTM, on the mitigation of consequences that may arise from individuals' use of DTM, and on the design of individual information systems with the goal of facilitating a

behavior change, specifically, regarding individuals' coping with stress. Overall, the research contained in this dissertation may promote the development of digital assistants that support individuals' in adopting a healthy DTM use behavior and thereby contribute to shaping a socio-technical environment that creates more benefit than harm for all individuals.

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List of Abbreviations

aIEI .... *Adapted Indoor Environmental Index*
AUC .... *Area under the curve*
AVE .... *Average variance extracted*
BCSS .... *Behavior change support system*
BDT .... *Boosted decision tree*
CO_2 .... *Carbon dioxide*
DecFo .... *Decision forest*
DF .... *Design feature*
DP .... *Design principle*
DR .... *Design requirement*
DSR .... *Design science research*
DSRM .... *Design science research methodology*
DTM .... *Digital technologies and media*
EFA .... *Exploratory factor analysis*
ESN .... *Enterprise social networks*
GHG .... *Greenhouse gas*
HBCSS .... *Health behavior change support system*
HR .... *Human Resources*
HVAC .... *Heating, ventilation, and air conditioning*
IAPI .... *Indoor Air Pollution Index*
IAQ .... *Indoor air quality*
ICT .... *Information and communication technology*
IDI .... *Indoor Air Discomfort Index*
IEI .... *Indoor Environmental Index*
IEQ .... *Indoor environmental quality*
IIS .... *Individual information system*
IS .... *Information system*
IT .... *Information technology*
JDCF .... *Java Data Collecting Framework*
MAE .... *Mean absolute error*
ppb .... *Parts per billion*
PSD .... *Persuasive systems development*

PSS .... *Perceived Stress Scale*
RMSE .... *Root-mean-square error*
SD .... *Standard deviation*
SDT .... *Self-determination theory*
SNA .... *Social network analysis*
SVM .... *Support vector machine*
TTS .... *Transactional Theory of Stress*
TVOC .... *Total volatile organic compounds*

1. Introduction

1.1. Motivation

As a wide-ranging socio-technical transformation, the digitalization has significantly influenced our lives. Today, a multitude of digital technologies and media (DTM) aim to support us in our work and private lives. Mobile technologies such as smartphones are our daily companions and personal assistants, the internet has long become our primary source of information, and social media helps us connect and stay connected to people across the globe. At the workplace, digital tools let employees finish their work more efficiently and industrial robots automate repetitive tasks. During the current COVID-19 pandemic, communication technologies such as videoconferencing tools have played a decisive role in making social distancing orders bearable and maintaining a productive work environment (Canale et al. 2021; Kniffin et al. 2021), while contact tracing apps have helped increase the safety of inevitable face-to-face contacts to other people (Lapolla and Lee 2020). Soon, progress in the field of explainable artificial intelligence will yield sophisticated DTM that cannot only deliver data-driven recommendations but also reason their recommendations to humans (Goebel et al. 2018). Altogether, these and many more positive effects of DTM on our work and private lives are the reason why many people can no longer imagine a world without DTM.

However, digitalization's impact on our lives is not entirely good. It has shaped a society in which large parts of our social interactions happen via DTM (Twenge and Spitzberg 2020). Individuals who feel insecure in using DTM, for example, elderly people, are at risk of being left behind and excluded from parts of public life and discourse when they refrain from using DTM (Friemel 2016; Nimrod 2018). But just using DTM is not yet sufficient: individuals must use the right DTM to stay connected with their social environment (Weinstein and Selman 2016a). Different social environments (e.g., work, friends, family) may require the use of different DTM. As new DTM emerge and spread at such a rapid pace, the preferred DTM may frequently change, causing that people constantly need to re-adapt to changing socio-technical environments (Lin 2014). At work, digital workplace technologies urge white-collar workers to multitask (Mark 2015). Social media notifications and online advertisements try to persuade individuals to interact with their peers or buy new products, ignoring that this may interrupt them in what they are currently doing (Chen et al. 2019). The overall volume and ubiquity of DTM requires individuals to process a broad and constant inflow of information demanding their interest, acknowledgment, or interaction (Anderson and Palma 2012). These examples demonstrate that the ongoing digitalization of our lives holds a plethora of demands that add to individuals' experience of non-digital demands (Ayyagari et al. 2011; Ismail 2017; Levin and Raffio 2019).

As a result, numerous publications in newspapers and scientific outlets emphasize that today's digital world can have detrimental effects on our well-being and health (Asmelash 2019; Cohut 2017; Cook 2016; Turel et al. 2021). Various studies relate the application of DTM at the workplace to an increase in individuals' experience of stress (Ayyagari et al. 2011; Ragu-Nathan et al. 2008; Tarafdar et al. 2019). But so-called *technostress* or *digital stress* may also arise from the private and voluntary use of DTM (Reinecke et al. 2017; Weinstein and Selman 2016a). Other scholars report that social media usage correlates with decreased self-esteem (Jan et al. 2017) and well-being (Orben and Przybylski 2019) in young adults. In addition, the widespread adoption and use of DTM have been linked to decreased mental health, including depression, in different age groups (Alhassan et al. 2018; Haidt and Allen 2020; Scott et al. 2017). While these examples demonstrate that DTM may severely impair individuals' health, the effects go beyond the individual. Bad mental health, for example, due to excessive stress, may also impact the economy and society by leading to an increasing number of sick days in the workforce, worse economic decisions, and rising expenses for public health (Goh et al. 2015; Stephens and Joubert 2001). As a result, the adverse effects of DTM are rapidly gaining scientific attention across disciplinary boundaries.

Combining insights from psychological, sociological, and (socio)technical perspectives, various characteristics of DTM have been linked to increasing individuals' demands (Becker et al. 2020; Reinecke et al. 2017; Steele et al. 2020; Weinstein and Selman 2016a). While the mere availability or ubiquity of DTM may already represent a burden individuals need to deal with, a multitude of demands arises from individuals' use of DTM (Tarafdar et al. 2019). Individuals typically use DTM to benefit from their functionality, which enables them, for example, to improve their work efficiency, connect to peers, or retrieve valuable information. Consequently, functionality is key for DTM producers to create economic value. While fee-based licensing is still the prevailing business model to create value from digital workplace technologies, especially for consumer-oriented DTM, other business models are on the rise. In particular, the monetization of user-specific data has become the essence of many business models (Fernández-Rovira et al. 2021), including those of big tech companies like Google, Facebook, or Amazon. The prototypical concept is simple: The company offers a service (e.g., a social network or a customer loyalty program) and collects data arising from the user’s interaction with the service (e.g., personal preferences or shopping behavior). Instead of (fully) charging the user for their service, they create value from the data, for example, by means of personalized advertising or product recommendations (Fernández-Rovira et al. 2021). Although this gives individuals seemingly free or cheap access to beneficial services, the price is higher than they perceive and bears the realistic risk that individuals feel invaded in their privacy (Ayyagari et al. 2011; Weinstein and Selman 2016a), regretting the disclosure of personal information.

Adding to this, a multitude of DTM today compete simultaneously for a scarce resource: the user’s attention (Crogan and Kinsley 2012). The more time users spend using their services, the more data can be turned into revenue. In this field of conflicting priorities, users are constantly forced to decide what to focus on. To gain an advantage over competitors, providers often strive to engage users to interact with their service as much as possible. Therefore, many DTM feature elements targeting to attract and capture the user’s attention. Despite numerous reports on the downsides of obtrusive user interface elements such as push notifications (Dodgson 2018; Glaveski 2019; Kushlev et al. 2016), many smartphone applications still make excessive use of such elements. In fact, various DTM providers have been criticized for doing too little against the addictive potential of their technologies (Alter 2017; BBC News 2018; The Economist 2016; Turel et al. 2011a). Although increasing public awareness of the problem has resulted in some improvements, of their own accord, DTM providers rarely take potentially harmful psychological effects of their technology into account.

Without a doubt, digitalization makes many people’s lives easier, better, and more convenient. However, it is also beyond doubt that everybody should do their best to prevent and mitigate digitalization’s risks and adverse effects on our lives. Scholars from various disciplines emphasize that research should place a stronger focus on the role of individuals in the digital world (Ameen et al. 2021; Baskerville 2011b). With its focus on examining and shaping the interaction between technology, people, and organizations (Avison and Elliot 2006; Hevner et al. 2004), the Information System (IS) discipline provides an important perspective fostering the creation of technologies that cater to the needs of individuals instead of corporations.

1.2. The Role of the Individual in Information Systems Research

More than half a century ago, organizations began to use information and communication technology (ICT) as a tool for increasing the efficiency of isolated operational activities. Soon, the use of computers spread across multiple organizational functions and persistently changed the way of working. This computerization of business is generally deemed as the impulse launching the inception of the IS discipline (Avison and Fitzgerald 1991; Hirschheim and Klein 2012). In this course, the IS field emerged from researchers from various disciplines sharing the objective to shed light on the application of ICT in social environments (Avison and Elliot 2006; Avison and Fitzgerald 1991). Due to its interdisciplinary origin, IS research draws theories and methods from various adjacent disciplines such as computer science, sociology, or psychology. However, it forms a distinct discipline because the mentioned disciplines focus either on the technology, the social environment, or the individual but not on their interaction. Early definitions reflect this interactional focus, stating that the subject of IS research is “the effective design, delivery, use and impact of information technologies in organizations and society” (Keen 1987, p. 3). This definition grasps very well that IS research can serve both analytical (analyzing the status quo) and transformational (designing the to-be) purposes. However, the assumption of a unidirectional effect from the technological to the social context today is outdated. Newer definitions suggest that an “information system is not the information technology (IT) alone, but the system that emerges from the mutually transformational interaction between the IT and the organization” (Lee 2004, p. 11), and point out that this “sociotechnical perspective captures the very essence of the IS discipline” (Sarker et al. 2019, p. 696). While the definition by Lee (2004) emphasizes the inseparability of information systems’ technological and social contexts, it employs a narrow view on which social contexts are of interest to the IS discipline. Sarker et al. (2019) widen this perspective, describing that the social context “includes humans (as individuals or social collectives) and their relationships and attributes” (Sarker et al. 2019, p. 698). Building upon these definitions, this dissertation adopts the perspective that IS research is invested in “study[ing] the applications of technology by organizations and society” (Avison and Elliot 2006, p. 5) through analyzing “interactions between people and [a social context] and technology” (Avison and Elliot 2006, 6f). In this analysis, both “instrumental outcomes such as efficiency and productivity *as well as* […] humanistic outcomes, such as well-being, equality, and freedom” (Sarker et al. 2019, 696, emphasis in original), are of interest.

However, IS literature is not distributed equally across this large field of research. Consequently, various researchers have expressed their concerns that certain perspectives are underrepresented in current literature. Concluding from a large-scale analysis of articles in two of the discipline's top journals, Sarker et al. (2019) criticize that most analyzed articles (56 %) take a predominantly social perspective in which technology is only a contextual aspect. Against this backdrop, they fear that the IS discipline is about to lose its socio-technical identity. In addition, they observed that an overwhelming majority of 87 % of the articles considered exclusively instrumental outcomes, neglecting that IS research has also devoted itself to serve humanistic goals (Sarker et al. 2019). Other scholars take a similar line, objecting that IS literature has long had a strong focus on organizational ICT use (Matt et al. 2019; Vodanovich et al. 2010).

However, today, the application of ICT is no longer limited to organizational use. Many years' technological progress allowed to put more computing power into ever-smaller devices. While early room-sized computers needed to be operated by up to twenty employees and, thus, were affordable only for large corporations, many modern ICT such as personal computers or smartphones are at the hand of single individuals (Baskerville 2011b). Today, the technical capabilities of a smartphone exceed those of early supercomputers (Offermann 2017), and no end of the progressively increasing computing power is in sight (Toumey 2016). As a result of this trend, ICT became accessible for smaller and smaller entities (Baskerville 2011b). This individualization of ICT use enables that today employees can often choose from various ICT to fulfill their work-related duties (Hirschheim and Klein 2012). But naturally, individuals' ICT use has not stopped at the organizational boundary (Baskerville 2011b). With the broad affordability of hardware, a multitude of new applications and services, also for private purposes, have been created and offered to the users. As a result of the digitalization of information, a new form of media, digital media, has emerged and placed beside traditional media such as television, radio, and newspaper. As a result, the term *information and communication technology* became too narrow to cover the full spectrum of the newly created offerings. Therefore, some researchers started to use the term *digital technologies and media*, or DTM, defined as "all the electronic devices (hardware) and applications (software) that use information in the form of numerical codes (usually binary codes), as well as all the media (i.e., means and channels of general communication in society) that are coded in formats that can be processed by these devices and applications" (Gimpel and Schmied 2019, p. 4), instead. In this work, the two terms and abbreviations – ICT and DTM – are used interchangeably. Private applications of DTM are manifold, ranging from the tracking and organizing of one's life and health over fast communication with peers to real-time information about current events. Facilitated by the digitalization of non-digital consumer products, there is also a passive use of DTM by individuals: For example, smart vehicles keep track of their environment and warn the driver about potential dangers, robots such as robot vacuum cleaners assist individuals in fulfilling their household duties, and smart thermostats improve the climate of their home. Individuals' application of DTM use resembles organizational use in many aspects. Most notably, it also involves a mutually transformational interaction between technology, people, and a social environment. For organizational DTM use, the social environment corresponds to the organization. For private DTM use, other social environments such as dyads, groups of people, or society supplant the organization's role. In social media, for example, individuals and technology form a socio-technical environment which creates effects on individuals that neither the technology alone nor the social surroundings alone would create.

Yet, the progressing individualization of DTM use has long been neglected in IS research (Baskerville 2011b; Matt et al. 2019). Although the IS field is not by definition limited to the application of DTM in organizations, the focal point of IS literature remained on organizational DTM use. In addition, many of the studies focusing on individuals considered them merely as end-users of organizational DTM (Baskerville 2011a), disregarding that individuals are not only consuming but, as a central element of the social context of IS, also contributing information (Baskerville 2011b; Sarker et al. 2019; Vodanovich et al. 2010). Following several calls in the last decade, research on individuals' DTM use is currently on the rise with intensified consideration of the emergent effects of DTM use on individuals arising when technology, people, and the social environment interact. Also, IS research's humanistic goals are recently coming more and more to the fore, with a growing research stream aiming to address digitalization's 'dark sides' (Turel et al. 2021). Already in 1991, Avison and Fitzgerald (1991) stressed that the field of "information systems has a rich multi-disciplinary nature, where 'human factors' are at least as important as 'technological factors'" (Avison and Fitzgerald 1991, p. 6). Now that DTM use is inevitable, this seems to become more relevant than ever before.

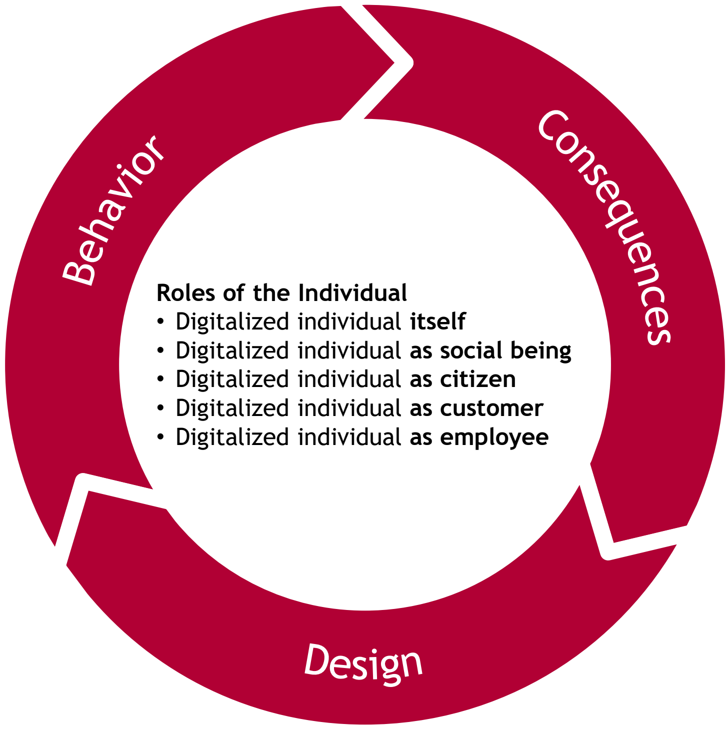


Figure 1: Research Framework for Analyzing Individuals' DTM Use, following Matt et al. (2019)

Aiming to promote and structure research on individuals' DTM use, Matt et al. (2019) proposed a framework for analyzing and shaping the ongoing digitalization of the individual (Figure 1). The framework describes two dimensions: the roles of the individual and the research angle. The first dimension, the individual's roles, builds upon the acknowledgment that the individual uses DTM in different roles. When using DTM for work, they act as an employee, when using DTM for the purpose of communicating with their peers, they act as a social being, and when using DTM to organize their life, they act for their own end. Similarly, they can use DTM in their roles as citizens or customers. The second dimension refers to the research angle taken. In an iterative order, research should take three mutually nurturing angles: First, studies should engage in analyzing people's behavior associated with their DTM use to understand "why and how individuals behave in certain ways and how this behavior can be influenced" (Matt et al. 2019, p. 317). Second, researchers should investigate what consequences arise from individuals' behavior and interaction with DTM for them or others. Lastly, the generated knowledge should inform the design of new technologies that exploit the technological opportunities with the aim to promote positive outcomes or address negative consequences of individuals' DTM use (Matt et al. 2019).

1.3. Aim and Outline of this Doctoral Dissertation

Recently, various scholars called for intensified IS research related to individuals' DTM use. Sarker et al. (2019) called upon IS researchers to find back to their tradition of socio-technical analysis, which considers the interface of the social and technological environment, the socio-technical environment, as the root of many DTM-use-related effects. In addition, Sarker et al. (2019) stressed that further efforts should be undertaken to investigate DTM's (potential) humanistic outcomes such as individuals' health, well-being, and job or life satisfaction. More specifically, Baskerville (2011a, 2011b) motivates IS researchers to engage in the analysis and design of individually owned and operated information systems. Similarly, Vodanovich et al. (2010) advocate for research efforts directed towards, what they call, ubiquitous information systems, arguing that a good understanding and appropriate design of DTM for individuals' use is currently gaining relevance with an increasing number of people growing up surrounded by DTM. Although rising awareness of the health risks of individuals' DTM use has brought up an increasing number of DTM aiming for the individual's good, various researchers call for a stronger focus on supporting individuals to prevent negative or promote positive consequences of their DTM use (Adam et al. 2017; Walsh and Groarke 2019). The popularity of fitness trackers or health-related smartphone applications demonstrates users' demands for assistance, specifically, in staying active, increasing well-being, or keeping track of their health (Piwek et al. 2016). Fitness trackers are just one example of systems that support individuals in changing their health behavior (Wu et al. 2016). Recent technological advances, particularly in the field of artificial intelligence and machine learning, enable more sophisticated approaches. Consequently, research exploring the technological capabilities by providing personalized real-time support is sought after (Walsh and Groarke 2019).

Responding to these calls for research, the dissertation at hand aims to contribute to IS research on the digitalization of individuals. It pursues the objective to facilitate a healthy use of DTM, particularly with respect to stress, for example, by means of changing individuals' behavior. Therefore, it explores various aspects of the use behavior, the consequences, and the design of DTM. The research in this dissertation is directed towards the creation of knowledge on how the technology, the individual, and the social environment can effectively influence the consequences of DTM use. Therein, it pursues primarily humanistic objectives targeting the mitigation of adverse outcomes with a focus on reducing individuals' stress. It combines behavioral and design science research as well as qualitative (e.g., workshops, interviews) and quantitative (e.g., lab or field experiments, survey research) research methods.

Following the framework of Matt et al. (2019), the dissertation addresses three key areas: it aims to (1) analyze individuals' behavior related to their use of DTM, (2) understand the consequences arising from their DTM use (including digital stress), and (3) shape a socio-technical environment which promotes the healthy use of DTM by reducing individuals' experience of stress. Thereby, it examines primarily individuals' roles as social beings or themselves (Matt et al. 2019).

First, the dissertation focuses on exploring DTM users' behavior. In two studies, it creates new knowledge on understanding how individuals behave when interacting with DTM, why they behave the way they do, and how their behavior can be influenced. Motivated by the variety of digital workplace technologies which offer employees different ways of pursuing their goals or performing their tasks (Köffer 2015), researchers strive for understanding the emergence and implications of users' various interaction behaviors related to these technologies. Although previous literature has already explored roles that users take in non-work-related DTM use, a digital workplace perspective is missing. Therefore, the first study presented in the dissertation analyzes what interactional roles DTM users can take at the digital workplace and what may influence their behavior. To provide real-world evidence, it builds on trace data from a popular digital workplace suite with 146 users in a single company. The empirical analysis yields eight user roles that advance the understanding of users' behavior at the digital workplace. In addition, qualitative interviews deliver first insights into what factors may influence this behavior. A second study adds another perspective and investigates how habitual behavior can be changed by means of DTM design elements. Real-time feedback has been discussed as a promising way to do so (Schibuola et al. 2016; Weinmann et al. 2016). In a field experiment, employees working at the digital workplace are provided with an external display that presents real-time feedback on their office's indoor environmental quality. The experiment examines if and to what extent the feedback influences their ventilation behavior to understand the effect of feedback as a means of influencing individuals' behavior. The results suggest that real-time feedback can effectively alter individuals' behavior, yet the feedback's effectiveness reduces over time, possibly as a result of habituation to the feedback.

Second, the dissertation creates new knowledge regarding the consequences of individuals' DTM use. Depending on individuals' behavior in relation to DTM, positive and negative consequences can arise. A frequently discussed consequence that digitalization has on individuals is digital stress. Recent research efforts strive to determine what measures individuals can take to effectively cope with digital stress (Salo et al. 2017; Salo et al. 2020; Weinert 2018). Further understanding of individuals' coping behavior is highly sought (Weinert 2018). A group at high risk of suffering from the adverse effects of digital stress is adolescents because they grow up using DTM daily and are still developing their identity, acquiring mental strength, and adopting essential social skills. Therefore, the third study included in this dissertation explores what strategies adolescents use to cope with the demands of their DTM use. Combining a qualitative and a quantitative study, the dissertation presents 30 coping responses used by adolescents, develops five factors underlying adolescents' activation of coping responses, and identifies gender- and age-related differences in their coping behavior.

Third, the dissertation presents new knowledge on the design of individual information systems supporting individuals in understanding and mitigating their perceived stress. Therefore, it explores the design and development of systems that assess stress and support individuals in coping with stress. Since stress is a problem with severe individual, economic, and societal consequences, efforts are taken to mitigate stress in both work and private life. Although DTM such as mobile devices reportedly contribute to stress in the form of digital stress, their powerful sensing capabilities may facilitate the creation of individual assistance systems (Adam et al. 2017). The possibilities include the development of systems aiming to support individuals in managing stress, for example, by initiating a sustainable change of behavior related to stress. Since there is currently limited understanding of how to develop such systems, this dissertation explores various facets of their design and development. As a first step, it presents the development of a prototype aiming for life-integrated stress assessment, that is, the mobile sensor-based assessment of an individual's stress without interfering with their daily routines. Data collected with the prototype yields a stress model relating sensor data to individuals' perception of stress. To deliver a more generalized perspective of the experiences made while designing and developing the prototype, the dissertation further presents a design theory based on a literature review of 136 publications targeting the mobile assessment of stress and five own prototyping activities. Including a design blueprint, design requirements, design principles, design features, and a discussion of potentially required trade-offs, the design theory may assist designers of mobile stress assessment systems in producing purposive and effective stress assessment components. A possible application purpose of mobile stress assessment is the production of mobile coping assistants. Aiming to assist individuals in effectively coping with stress and preventing future stress, a mobile coping assistant should recommend adequate coping strategies to the stressed individual in real-time or execute targeted actions within a defined scope of action automatically. While the implementation of a mobile coping assistant is yet up to future research, the dissertation presents an abstract design and algorithm for selecting appropriate coping strategies.

In sum, this dissertation contributes to IS research by delivering knowledge on how individuals interact with DTM and how this interaction can be healthy by preventing excessive stress. Therefore, it presents newly generated knowledge on individuals’ behavior related to DTM, the mitigation of DTM use’s adverse outcomes, and the design of individual information systems supporting stress management. Chapter 2 delivers foundational knowledge on individual information systems, information systems supporting a behavior change, and (digital) stress theory as well as an introduction into the IS discipline’s diverse methodological approaches for analyzing and designing socio-technical systems. Chapter 3 examines how DTM users behave and interact in DTM-enabled collaborative work settings and how they adapt their venting behavior as a response to real-time feedback on air quality. Chapter 4 examines adolescents’ experience of digital stress resulting from their interaction with DTM and investigates how they cope with digital stress. Chapter 5 explores how mobile systems can assess their user’s stress and how information systems can build on that to support individuals’ coping with digital stress. Chapter 6 draws meta-inferences synthesizing the various perspectives, discusses the findings with respect to limitations, and gives an indication of how further research can build on the work presented here. Figure 2 visualizes the structure of this dissertation and illustrates how the chapters relate to the theoretical framework from Matt et al. (2019).

During the process of developing this dissertation, parts of Chapters 3, 4, and 5 were published in journals and conference papers as part of a regular scholarly discourse or are under consideration for joint publications with coauthors.[1] Major parts of Chapter 3 conform with Frank et al. (2017) and Bitomsky et al. (2020). Major parts of Chapter 4 conform with Schmidt et al. (2021). Major parts of Chapter 5 conform with Gimpel et al. (2019b), Bonenberger et al. (2021), and Schmidt et al. (2022).

[1] This doctoral thesis follows the “Promotionsordnung der Mathematisch-Naturwissenschaftlich-Technischen Fakultät der Universität Augsburg (in der Fassung vom 21.5.2014)“ and the “Handreichung des Instituts für Materials Resource Management (MRM) für Doktorandinnen und Doktoranden zur Einbindung von Vorveröffentlichungen in eine monografische Dissertation im Rahmen einer Promotion zum Dr.-Ing. an der Mathematisch-Naturwissenschaftlich-Technischen Fakultät (MNTF) der Universität Augsburg (in der Fassung vom 09.01.2020)“.

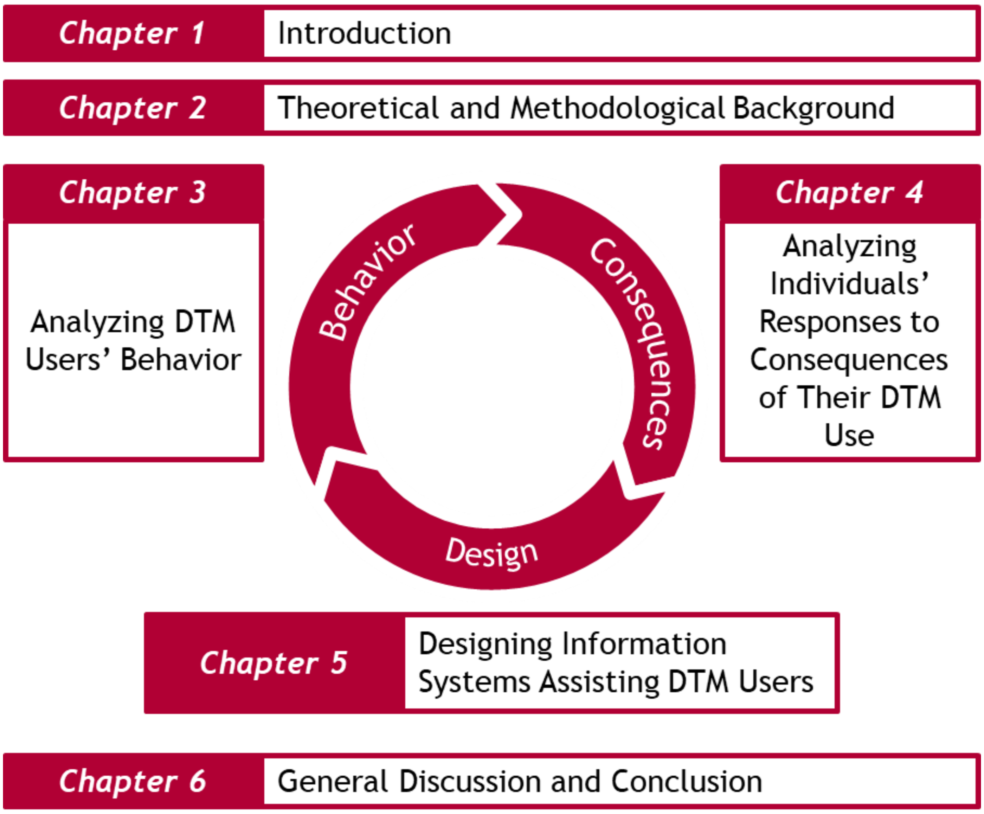


Figure 2: Structure of this Doctoral Dissertation

2. Theoretical and Methodological Background

2.1. Individual Information Systems

Although the predominant focus of IS research has long been on organizational DTM use, the permeation of private life with DTM did not remain unnoticed by IS scholars. Already in 1996, Silberschatz and Zdonik (1996) envisaged that there will soon be *personal information systems* that provide “information tailored to an individual and delivered directly to that individual via a portable, personal information device […] such as a personal digital assistant, handheld PC, or a laptop” (p. 770). Although this vision came true less than a decade later, the analysis of the socio-technical effects of this change remained rather absent from IS research. Yet, this changed at the beginning of the 2010s. Vodanovich et al. (2010) called for intensified efforts targeted to examine “ubiquitous information systems used by digital natives for professional and personal purposes at the office and at home” (p. 713). A year later, Baskerville (2011a, 2011b) strived to draw IS researchers’ attention to what he called *individual information systems* (IIS). According to his definition, an individual information system is an “activity system in which individual persons, according to idiosyncratic needs and preferences, perform processes and activities using information, technology, and other resources to produce informational products and/or services for themselves or others” (Baskerville 2011a, p. 1). While the definition at first seems unspecific regarding which information systems it includes, it reveals that the core aspect of IIS is individuals’ idiosyncratic use of them, regardless of the context it is used in. Thus, IIS is not a new category of IS. Instead, an individual’s *IIS portfolio* consists of the total of information systems that the individual interacts with for work and private purposes (Baskerville 2011b). Therefore, a variety of different information systems, including devices (e.g., personal computers, smartphones, wearables, smart things), applications (e.g., mobile apps, computer software), media (e.g., e-mail, social networks, videogames), and services (e.g., cloud storage, web services) can be part of this IIS portfolio.

This is a rather new perspective to IS research. In the past, many IS studies considered humans primarily as end-users of (organizational) DTM. However, this perspective falls short because individuals are not only passive users or consumers of DTM but their active interaction with DTM shapes the socio-technical environments that we encounter in society, organizations, and smaller groups (Baskerville 2011b). When interacting with DTM, individuals often produce, record, exchange, or process information, thus, contributing to the information systems they use (Baskerville 2011a). The IIS perspective places the individual in the center of focus. IIS research examines information systems and their socio-technical environment from the perspective of individuals. Forecasting that privately used IS will be making major inroads, Baskerville (2011b) stresses that deeper understanding is needed what effects IISs have on individuals and how individuals construct, control, and optimize their IIS architecture. Gaß et al. (2015) expand on this and elaborate on the basis of sociological processes how individual characteristics and social contexts influence an individual's portfolio of IIS (Figure 3). Thereby, the *individual characteristics* refer to the values, attitudes, moral, knowledge, and skills of an individual. A *social context* refers to values, attitudes, moral, knowledge, and skills shared within a certain group the individual is part of. Individuals can be part of multiple social contexts, for example, work, family, and friends as well as other areas such as sports clubs or subgroups of these contexts.

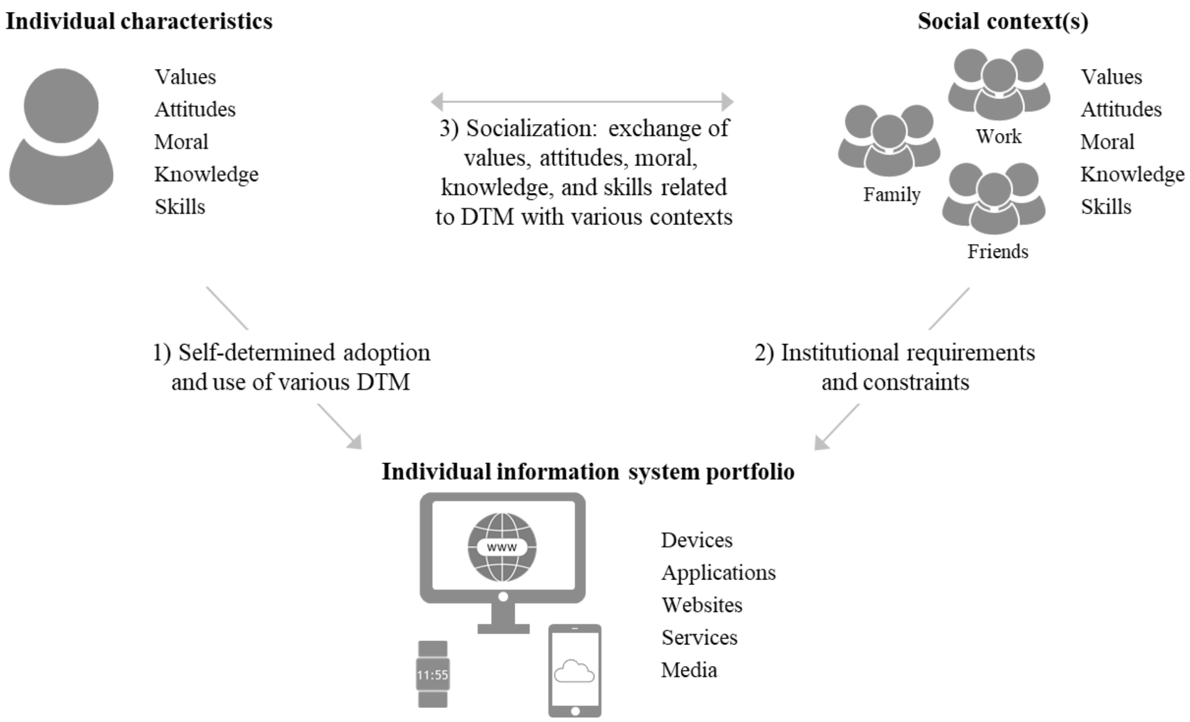


Figure 3: Processes Determining Individual Information System Portfolios, following Gaß et al. (2015)

Gaß et al. (2015) describe three key relations that influence the composition of individual information system portfolios. First, the individual characteristics influence the IIS portfolio through the self-determined adoption and use of DTM due to idiosyncratic needs and preferences. This is the case when an individual decides to use (or terminate their use of) a specific DTM (e.g., a mobile to-do list app) because they perceive it as (not) helpful for accomplishing a specific goal (e.g., keeping track of their to-dos). Second, a specific social context may impose institutional requirements and constraints that require individuals to alter their IIS portfolio. Classic examples for this relation are requirements concerning the use of specific DTMs at work. Yet, such impulses may also come from private social contexts, for example, when friends decide to communicate via a specific communication service that the individual might not have preferred but uses to not miss out on group-related news. Third, in a process of socialization, the individual characteristics and social contexts influence each other by exchanging DTM-related values, attitudes, moral, knowledge, and skills. For example, an individual may internalize the group preference for a specific DTM, spread the word, and further distribute the DTM to other social contexts.

Focusing on individuals' use of DTM, this dissertation adopts the IIS perspective in two ways: it views DTM from the perspective of individuals, and it aims to design information systems that add to individuals' IIS portfolios. Specifically, the dissertation aims at designing behavior change support systems that assist individuals' coping with stress. The next section introduces health behavior change support systems as a specific type of individual information systems.

2.2. Health Behavior Change Support Systems

With the increasing individualization of DTM use, computer technologies also started to be used for the purpose of influencing what individuals think and do. Fogg (1998, 2003) introduced the term *persuasive technology* to refer to "an interactive technology that attempts to change [a person's] attitudes or behaviors in some way" (Fogg 1998, p. 225). Thereby, persuasive technologies step into a long tradition of persuasion as a subject of research in social psychology. Independent of technology, it is part of human social behavior to constantly try persuading others by communicative means. Persuasive communication has been defined as "any message that is intended to shape, reinforce, or change the responses of another, or others" (Stiff and Mongeau 2016, p. 4). Another definition describes persuasion as "a symbolic process in which communicators try to convince other people to change their attitudes or behaviors regarding an issue through the transmission of a message in an atmosphere of free choice" (Perloff 1993, 8). Despite similar goals, persuasion does not include forceful measures such as coercion or deception. From these definitions, it becomes clear that persuasion is an intentional behavior.

According to Fogg (1998), technologies can also be persuasive. However, since technology does not have intentions, the intentionality comes from "those who create, distribute, or adopt the technology […] with an intent to affect human attitudes or behaviors" (Fogg 1998, p. 226). Persuasive technologies can, for example, be systems that encourage individuals to complete their tasks, motivate them to do sports, or promote and facilitate a healthy diet. In his view, technologies (not limited to persuasive technologies) can serve three functions: they can act as *tools*, *media*, or *social actors* (Fogg 1998). In their function as tools, technologies increase individuals' capabilities, allowing them to do things more easily or extending the range of things they can do. In their function as media, technologies provide experiences emerging from symbolic or sensory content. In their function as social actors, technologies create relationships with individuals by means of appearance and social interaction. All three functions can be used for persuading individuals to change their attitudes or behaviors but appeal to humans in different ways. Persuasive tools make target behavior easier, provide information or guidance, increase self-efficacy, or change mental models. Persuasive media motivate individuals to explore, enable hands-on or visual learning and experiences, or promote an understanding of causal relations. Persuasive social actors model a target behavior or attitude, reward and feedback positive behavior, or provide social support (Fogg 1998).

Later, Oinas-Kukkonen (2010) introduced the term *behavior change support system* (BCSS) to refer to a specific instance of persuasive technology. He defined a BCSS as "a socio-technical information system with psychological and behavioral outcomes designed to form, alter or reinforce attitudes, behaviors or an act of complying without using coercion or deception" (Oinas-Kukkonen 2013, p. 1225). The two enumerations included in the definition can serve as a classification to describe BCSSs' possible outcomes and types of change (Table 1).

	C-Change (compliance)	**B-Change (behavior)**	**A-Change (attitude)**
F-Outcome (form)	Forming an act of complying	Forming a behavior	Forming an attitude
A-Outcome (alter)	Altering an act of complying	Altering a behavior	Altering an attitude
R-Outcome (reinforce)	Reinforcing an act of complying	Reinforcing a behavior	Reinforcing an attitude

Table 1: Outcome/Change Matrix of BCSSs, following Oinas-Kukkonen (2013)

An F-Outcome (for forming) is realized when the system forms a psychological or behavioral pattern that has not been there before (e.g., resist the urge to smoke). An A-Outcome (for altering) is achieved when the system alters an existing psychological or behavioral pattern (e.g., drink more water). An R-Outcome (for reinforcing) is obtained when the system reinforces a psychological or behavioral pattern to increase its resistance to change (e.g., keep doing sports). A C-Change aims to influence the user's compliance with requests (e.g., take a medicine). A B-Change aims to influence the user's behavior enduringly (e.g., keeping track of to-dos). An A-Change aims to influence the user's attitudes (e.g., raise awareness of health risks of a specific behavior). Often B- and A-Change go hand in hand to achieve a sustainable change of behavior, especially in cases where the current behavior is hard to change, like in the case of addictions (Oinas-Kukkonen 2010, 2013).

A specific type that is prevailing in BCSS literature is health behavior change support systems (HBCSSs) (Kelders et al. 2016). They are BCSSs aiming for a behavioral change in the domain of health. HBCSSs have been examined and developed for a wide variety of target groups and areas of individual health, including smoking cessation (Walters et al. 2006), depression treatment (Kuonanoja et al. 2015), and coping with substance (VanDeMark et al. 2010) or technology addiction (Alrobai et al. 2016).

Various psychological processes influence how individuals internalize beneficial health behavior (Schwarzer 2008). Most importantly, health self-regulation is a "motivational, volitional, and actional process of abandoning […] health-compromising behaviors in favor of adopting and maintaining health-enhancing behaviors" (Schwarzer 2008, p. 2). Dividing self-regulation into its components, an actional change of behavior requires motivation and volition. The pre-intentional motivation phase aims to form a behavioral intention (goal setting). The post-intentional volition phase translates the intention into actual behavior. Motivation and volition are influenced by various factors, specifically, outcome expectancy, perceived self-efficacy, and perceived risk. In this interplay, HBCSSs must set the ground for successful motivation and volition to facilitate a sustainable behavior change.

One of the most renowned theories for explaining motivation is the self-determination theory (SDT) from Deci and Ryan (1985, 2000). According to the SDT, three psychological needs are critical for the development of motivation and internalization of behavior: *autonomy*, *competence*, and *relatedness*. The need for autonomy involves that an individual feels able to decide on their own actions. The need for competence requires that an individual feels able to perform a behavior and achieve the desired outcome. The need for relatedness demands that an individual feels connected to and understood by people who are important to them. The fulfillment of those three needs creates an environment in which individuals are more likely to strive for a certain behavior and master a change of their behavior (Deci and Ryan 1985, 2000; Patrick and Williams 2012).

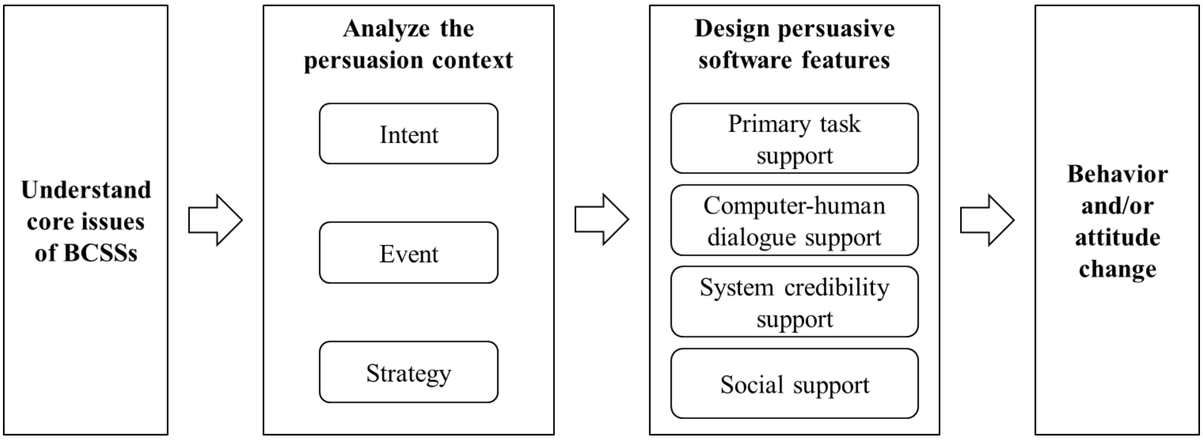


Figure 4: Persuasive System Development Model, following Oinas-Kukkonen and Harjumaa (2009)

To structure and facilitate the development of (H)BCSSs, Oinas-Kukkonen and Harjumaa (2009) proposed the Persuasive Systems Development (PSD) model, which describes three phases of system development (Figure 4). In the first phase, BCSS designers should become aware of seven core issues of BCSS design (Table 2) (Oinas-Kukkonen and Harjumaa 2009).

Core issue from Oinas-Kukkonen and Harjumaa (2009)	**Consequence**
IT is never neutral.	Persuasion is not a single act but a process. BCSSs should be flexible to changing goals.
People like their views about the world to be organized and consistent.	BCSSs may make individuals aware of cognitive dissonance in one's behavior to motivate a behavioral change.
Direct and indirect routes are key persuasion strategies.	Individuals process information differently. BCSSs should use various ways to consider interindividual differences.
Persuasion is often incremental.	Behavior change is inert. BCSSs should provide incremental rather than one-step suggestions.
Persuasion through persuasive systems should always be open.	User's trust is important. BCSS designers should make their intentions and information sources transparent.
Persuasive systems should aim at unobtrusiveness.	BCSSs should not disturb their users and be sensitive to opportune and inopportune moments.
Persuasive systems should aim at being both useful and easy to use.	To be persuasive, BCSSs should strive for high software quality, especially in terms of usability and usefulness.

Table 2: Core Issues Relevant to the Design of BCSSs, following Oinas-Kukkonen and Harjumaa (2009)

In the second phase of the PSD, BCSS designers should analyze the context of the persuasion. Specifically, they should analyze the *intent*, the *event*, and the *strategy*. The intent refers to the persuader in Fogg's (1998) framework (who creates, distributes, or adopts the technology?) and the targeted behavior change according to the outcome/change matrix in Table 1. The event includes the analysis of the use context (what are relevant characteristics of the problem domain (e.g., individual health)?), the user context (what are relevant characteristics of the user (e.g., goals, motivation)?), and the technology context (what are relevant characteristics of the technological environment?). The strategy concerns the message (what message should be transported?) and its route (how is the message transported to the user?).

The third phase of the PSD comprises the actual design and development of the BCSS. An important step is the definition of functional and non-functional requirements. Building on the analysis of the persuasion context in phase 2, requirement definition involves the selection of design features used for persuasion. Oinas-Kukkonen and Harjumaa (2009) propose four categories (primary task support, computer-human dialogue support, system credibility support, and social support) and several persuasive design features for each of these categories (e.g., personalization, rewards, verifiability, and social comparison). Additional input regarding relevant design features can be taken from two closely related research streams, namely, *gamification* and *(digital) nudging*. Both ideas have been related to behavior change (Schmidt-Kraepelin et al. 2019; Vlaev et al. 2016) and motivation through self-determination (Arvanitis et al. 2020; van Roy and Zaman 2017). Gamification involves "the use of game design elements in non-game contexts" (Deterding et al. 2011, p. 12) and is typically used to induce a behavior change by motivating individuals through DTM to do something (Sailer et al. 2017). Similarly, nudging refers to the use of a so-called nudge as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler and Sunstein 2009, p. 6), for example, to change their health behavior (Vlaev et al. 2016). Its digital equivalent is digital nudging which uses user-interface design elements for this purpose (Weinmann et al. 2016).

Although HBCSSs are primarily designed to serve a good purpose, they pose a variety of ethical challenges (Fogg 2003; Tengland 2016). Previous literature has highlighted various aspects relevant to the ethics of behavior change techniques, including the engagement of stakeholders (Davis 2009), the absence of adverse side-effects (Fogg 2003), and the voluntariness of use (Smids 2012; Tengland 2016). Although scholars uniformly emphasize the importance of considering ethics, they have not yet agreed upon a uniform approach to resolve ethical issues in persuasive behavior change technology (Kight and Grim-Hansen 2019).

These theoretical foundations on the design of persuasive technologies in general and HBCSS in particular lay important groundwork for both the analysis of the effect of real-time feedback on indoor environmental quality as well as the design of a mobile coping assistant. With its objective to assist individuals in coping with stress, the mobile coping assistant represents an HBCSS that persuades individuals to cope with stress by delivering targeted and real-time recommendations. To prepare appropriate coping recommendations, further theoretical knowledge on stress, digital stress, and coping is required. The following section delivers these theoretical foundations.

2.3. DTM Users' Stress

A factor strongly contributing to individuals' decreased health is *stress*. Due to the rising complexity and mental load in work and private life, the number of people regularly experiencing stress is increasing (Ferreira et al. 2008). The COVID-19 pandemic has further accelerated this trend (American Psychological Association 2020; Salari et al. 2020), with some professions and groups of people (e.g., healthcare workers, parents) experiencing extraordinary demands as a result of the pandemic situation (Bohlken et al. 2020; Liu et al. 2021). While the occurrence of stress is not yet a health problem and stress is not necessarily bad, the consequences of excessive stress may be detrimental to individuals' health (Quick et al. 1987). Besides adverse individual outcomes, undue stress may also create a societal and economic problem when individuals develop chronic psychological and physiological illnesses, including burnout, are frequently absent from work, and need medical treatment (Goh et al. 2015). Therefore, the effective management of stress is deemed a highly important public health challenge of our time (Riedl 2013). A modern form of stress is *digital stress*, which refers to stress due to the presence and use of DTM (Fischer et al. 2021). With the rising prevalence of DTM in both work and private life, digital stress has gained importance and today constitutes a significant share of individuals' perception of stress. This section first gives an introduction to human stress theory and then expands further on digital stress.

Human Stress

Over the years, stress has been extensively researched, especially from psychological and biological angles. As a result, there is a multitude of definitions and theories that deliver related but different conceptualizations of stress. Early definitions understood stress either as an environmental stimulus that requires psychological readjustment (Holmes and Rahe 1967) or as “a non-specific response of the body to any demand” (Selye 1956). The former definition, the stimulus-based view, attributes a rather passive role to the individual, assuming that the magnitude of stress is primarily determined by the event that “requires a significant change in the ongoing life pattern of the individual” (Holmes and Rahe 1967, p. 217). In contrast, the latter, the response-based view, regards the body’s subconscious, physiological response to the environment as indicative of stress. While both theories contributed to understanding individuals’ experience of stress, they are insufficient to explain individual differences in stress perception (Rout and Rout 2002). It has been noted that different people in the same situation do not experience the same level of stress – challenging the stimulus-based view – and that the same persons respond differently to different situations – challenging the response-based view – (Rout and Rout 2002). This suggests that it is neither only the environment nor only the individual that determines stress but an interaction of the two. Consequently, Lazarus and Folkman (1984), building on Lazarus (1966), have developed the Transactional Theory of Stress (TTS), which today is one of the most referenced frameworks for understanding human stress. It views stress as occurring “when an individual perceives that the demands of an external situation are beyond his or her perceived ability to cope with them” (Lazarus 1966, p. 9). Thus, it conceptualizes stress as the result of a transaction between an individual and their environment. This transactional model of stress (Figure 5) is described in detail in the following.

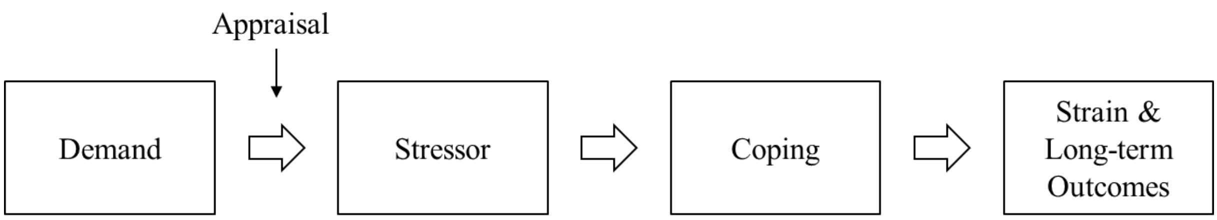


Figure 5: Transactional Model of Stress

It is an inherent task of the human body to maintain a relatively stable state, so-called *homeostasis* (Cannon 1929). In everyday life, individuals are exposed to a myriad of external or internal stimuli, or *demands*, that may potentially threaten this homeostasis and represent a *stressor* (Varvogli and Darviri 2011). For a long time, researchers supposed that *major life events* (e.g., death of a loved one, divorce, or severe illness) demanding a change of life are mainly responsible for individuals’ experience of stress (Holmes and Rahe 1967; Wagner et al. 1988). At the beginning of the 1980s, the focus shifted more towards *daily hassles* as stressors “manifested in the immediate context of thought, feeling, and action” (Lazarus and Folkman

1984, p. 231). Consequently, various studies examined the relationship between the two and found that daily hassles mediate the effect of major life events on stress (Kanner et al. 1981; Wagner et al. 1988), and thus, are a better predictor of individuals' stress (DeLongis et al. 1982). Almeida et al. (2002) distinguish six categories of daily hassles: arguments or tensions (e.g., disagreements with friends, family issues), work or school (e.g., work overload, timing or scheduling issues), home (e.g., financial problems, household repairs), health care (e.g., accident or illness), network (e.g., bad health of others), and miscellaneous (e.g., traffic, bad world news). All these stressors may result in stress but do not necessarily do so.

To determine whether they are potentially stressful, each demand undergoes a subconscious *appraisal* mechanism comprising two steps. *Primary appraisal* evaluates if a demand is benign-positive, irrelevant, or stressful (Folkman and Lazarus 1985). If it is benign-positive or irrelevant, it is not relevant for the individual's stress perception. If it is stressful, a further classification into one of the categories challenge, threat, or harm/loss takes place (Folkman and Lazarus 1985). Stressors are appraised as harm/loss when the damage has already occurred, for example, in the form of an injury, illness, or the death of a friend. An appraisal as a threat refers to the potential for future harm or loss. In contrast, a stressor appraised as a challenge offers potential for individual growth. In addition, *secondary appraisal* evaluates if the individual has enough available resources and options to cope with the demand. Although the two steps of appraisal influence each other, there is no temporal order implied.

To overcome stress, individuals activate a mechanism called *coping* targeting to counter the stressful demands. Thereby, coping refers to "constantly changing cognitive and behavioral efforts exerted to manage specific external and/or internal demands that are appraised as taxing or exceeding the resources of the person" (Lazarus and Folkman 1984, p. 141). Effective coping builds on the individual's available resources (e.g., knowledge, skills, capabilities, mental state) and has the potential to prevent or reduce adverse stress outcomes. Two coping styles are prevailing: problem-focused coping and emotion-focused coping (Lazarus and Folkman 1984). Problem-focused coping attempts to change or influence the problematic demand, whereas emotion-focused coping aims at manipulating the stress-related emotional arousal. Across the two overarching styles, individuals can activate a broad range of coping responses (Carver et al. 1989; Carver 1997; Skinner et al. 2003), such as avoiding the stressor or asking for instrumental support as problem-focused approaches (Thoits 1995) and positive thinking or seeking emotional support as emotion-focused coping responses (Carver et al. 1989). Which coping responses an individual activates depends on various factors, including individual characteristics (e.g., age, gender, personality, habits) and characteristics of the socio-technical context (e.g., stressor(s), time, ICT use) (DeLongis and Holtzman 2005; Salo et al. 2017).

To structure the field of coping, Skinner et al. (2003) propose twelve families of coping as higher-order categories of coping (Table 3) organized around three dimensions[2]: challenge vs. threat (i.e., the individual can handle the demand vs. is overwhelmed by the demand), the target addressed by the coping reaction (self or context), and three needs individuals strive for (competence, relatedness, and autonomy). The latter dimension refers to the three innate psychological needs introduced by Ryan and Deci (2000) in the Self-determination Theory, which provides explanations for behavior changes. The fulfillment of the needs for competence (i.e., ability to effectively perform a behavior and control the outcome), relatedness (i.e., social connection to and interaction with others), and autonomy (i.e., power to make own choices) enables intrinsically motivated behavior changes as well as the integration of extrinsically motivated behavior (Ryan and Deci 2000). Each coping family represents a set of functionally similar coping strategies (e.g., for problem-solving: planning, logical analysis, or diligence) contributing to one of the three overarching *adaptive processes* that enable behavior changes by addressing the needs for competence, relatedness, and autonomy. The coping families serve different functions in the adaptive processes. Four families are each grouped into three main adaptive processes (second column in Table 3): adaptive processes that coordinate an individual's activity with the eventualities in the environment (competence), adaptive processes that coordinate the individual's reliance on others with the social resources in the environment (relatedness), and adaptive processes that coordinate an individual's preferences with the options available in the environment (autonomy) (Skinner et al. 2003). For example, *problem-solving* allows an individual to alter or modify activities to be effective in the existing environment, whereas *information-seeking* aims to discover alternatives. Both families of coping foster more structured and effective activities in situations taken as a challenge but differ in the addressed target (*problem-solving*: self; *information seeking*: context) (Skinner et al. 2003).

[2] Large parts of this paragraph and the following table are identical to the author's own work published as Schmidt et al. (2022).

Family of Coping	Adaptive Process	Function in AP
Problem-solving [1, S]	Coordinating individuals‘ activities	Modify activities to be effective
Information Seeking [1, C]		Find additional alternatives
Helplessness [2, S]		Find limits of activities
Escape [2, C]		Escape non-contingent environment
Self-reliance [1, S]	Coordinating individuals’ reliance on others	Protect available social resources
Support Seeking [1, C]		Use available social resources
Delegation [2, S]		Find limits of resources
Social Isolation [2, C]		Withdraw from the unsupportive context
Accommodation [1, S]	Coordinating individuals‘ preferences	Flexibly adjust preferences to options
Negotiation [1, C]		Find new options
Submission [2, S]		Give up preferences
Opposition [2, C]		Remove constraints

Note: 1) Challenge, 2) Threats, S) Self, C) Context

Table 3: Families of Coping and Their Function in Adaptive Processes

If the two appraisals combined yield an imbalance between the demand side (primary appraisal) and the resources side (secondary appraisal) and the individual’s coping efforts are not successful, a *stress reaction* sets in (Lazarus and Folkman 1984). The body releases the hormone adrenaline to prepare for an imminent “fight-or-flight” response by increasing vital functions such as breathing and heartbeat and inhibiting irrelevant functions such as digestion (Gunnar and Quevedo 2007). In addition, the primary stress hormone cortisol is released to provide the body with extra energy and keep the alert state up (Thau et al. 2019). When the cortisol level decreases, this is the signal for the body to return to homeostasis (Gunnar and Quevedo 2007). The stress reaction may produce a variety of short-term responses, including physiological, psychological, and behavioral *strain* (Kahn and Byosiere 1992; Olusoga et al. 2010). Examples of physiological responses are increases in heart rate (Trimmel et al. 2003), blood pressure (Boucsein 2009), and skin conductivity (Riedl et al. 2013). Psychological responses are, above all, bad emotions such as anger or frustration and negative cognitions such as worry or self-doubt (Olusoga et al. 2010). Behavioral responses include reduced work engagement, nervous habits, and dysfunctional social behavior (Sandi and Haller 2015). If individuals experience stress constantly or perceive excessive levels of stress, long-term consequences (e.g., psychological illnesses such as burnout or depression) may arise (Hammen 2005).

Yet, the effects of stress are not necessarily bad. In 1974, Hans Selye refined his perspective on stress and introduced two types of stress: *eustress* (“good stress”) and *distress* (“bad stress”)

(Selye 1974). While it is disputed if there is a conceptual difference between the two terms (Bienertova-Vasku et al. 2020; Kupriyanov and Zhdanov 2014), researchers agree that stress may result in positive and negative outcomes. Since stress serves the basic function to maximize performance in handling stressful demands by suppressing competing processes (Gunnar and Quevedo 2007), it puts individuals into the position to perform their tasks more efficiently (Benson and Allen 1980). A common view is that eustress occurs when an individual reacts to a stressor with positive responses (e.g., increased productivity, positive feelings), while distress produces negative outcomes (e.g., decreased productivity, negative feelings) (Lazarus 1993). The outcomes of stress are dependent on a variety of factors. Eustress and distress have been linked to the mechanism of primary and secondary appraisal. Various studies indicate that threat and harm/loss appraisals are more often associated with bad effects on individuals' health and performance, whereas challenge stressors are more likely to produce desirable effects, including task engagement and positive affect (Maier et al. 2003; O'Connor et al. 2010). However, the secondary appraisal also plays in. An individual who is confronted with a threat stressor but perceives that they have enough resources to deal with the demand might effectively avert adverse stress outcomes. Likewise, a challenging demand may turn into a threat if not enough resources for coping are available (Folkman and Lazarus 1985). Another perspective states that there might be an (individual) optimal level of stress in which the individual achieves maximum performance (Benson and Allen 1980). Every stress up to this optimal level acts as eustress; every stress exceeding this optimal level produces adverse outcomes and acts as distress. However, Bienertova-Vasku et al. (2020) argue that these explanations disregard the factor of time. At the example of a closing work deadline, they describe that the same stressor may first cause anxiety and reduced efficiency due to the upcoming deadline, then a boost of productivity near the deadline, and finally, a feeling of exhaustion with reduced work performance immediately after the deadline. Because of this and other points of critique, they suggest avoiding the terms 'eustress' and 'distress' and refer only to 'stress' instead (Bienertova-Vasku et al. 2020).

Digital Stress

Already in the 1980s, psychologist Craig Brod noted that the progressing use of computers at the workplace comes with increased mental costs for employees, leading to a rising perception of stress. In his 1984 book, Brod introduced the term *technostress,* which he defined as "a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner" (Brod 1984, p. 16). However, this definition dates back to a time in which personal computers were still rare and the use of ICTs was limited to a few workplaces. Although Brod's definition still holds historical value, it took over 20 years for technostress research to gain momentum. In the meantime, the use of ICTs has changed from a niche role to a frequent occurrence for most employees. Hence, Ragu-Nathan et al. (2008) updated the definition of technostress to "stress experienced by individuals due to the use of ICTs" (p. 418). In the following, a multitude of IS studies investigated technostress with a predominant focus on the workplace. Recently, anchored in communication and psychology and conceptually detached from technostress research, another research stream dealing with the stressful effects of DTM has formed. Firming under the name *digital stress*, they refer to "stress reactions elicited by environmental demands originating from ICT use" (Reinecke et al. 2017, p. 92). While this definition is very similar to the well-known definitions used in IS research, the term 'digital stress' is broader in the sense that it terminologically includes digitalization at large as a source of stress rather than focusing only on its impact in work environments. Further, the term digital stress is less technology-centric than the term technostress and thereby better represents the fact that it is not so much the technology that creates the stress but rather our individual and collective use of and perspectives on the technologies and media. In this thesis, the two terms are used synonymously.

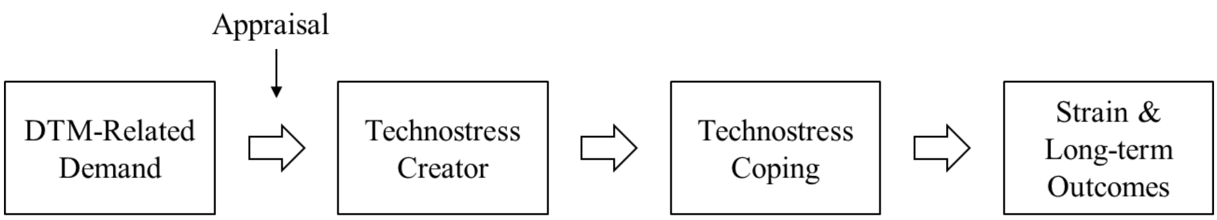


Figure 6: Transactional Model of Digital Stress

Although the TTS transfers seamlessly to DTM-related stress (Tarafdar et al. 2019), technostress research uses a slightly different terminology (Figure 6), mainly because it targets not only understanding the psychological processes but also shaping individuals' socio-technical environment. In technostress, individuals are exposed to a variety of *DTM-related demands* (in TTS: stimuli/demands). If appraised as stressful, demands may act as *technostress creators* (in TTS: stressors) that need to be *coped* with to prevent *strain* and adverse *long-term outcomes*. To better describe the socio-technical environment, technostress research adds a concept to the TTS. While in TTS, demands may stem from a plethora of internal and external (environmental) sources, DTM-related demands in technostress research stem particularly from technology-environmental conditions, referring to potentially stress-relevant conditions of the socio-technical environment (Tarafdar et al. 2019). Examples are the ubiquity of ICTs (Ayyagari et al. 2011) or frequent changes to the ICT environment (Beaudry and Pinsonneault 2005).

As one of the focal points of technostress research, digital stress and technostress literature have identified a variety of technostress creators (e.g., Ayyagari et al. 2011; Fischer et al. 2021; Ragu-Nathan et al. 2008; Weinstein and Selman 2016a)[3]. Organizational technostress literature has produced a rich set of technostress creators relating to demands which arise from the use of ICT at work (Ayyagari et al. 2011; Fischer and Riedl 2015; Ragu-Nathan et al. 2008; Tarafdar et al. 2007; Tarafdar et al. 2010; Tarafdar et al. 2011): *Techno-overload*, *techno-invasion*, *techno-complexity*, *techno-uncertainty*, *techno-unreliability*, *techno-insecurity*, and *invasion of privacy*. While research on technostress from private ICT use is less widespread, several technostress creators from the organizational context (*overload*, *invasion*, *complexity*, *uncertainty*, *invasion of privacy*) have been transferred to and confirmed for the use of private ICT such as social networks (Maier et al. 2012, 2015a; Maier et al. 2015b; Salo et al. 2019) and smartphones (Vahedi and Saiphoo 2018). In an adolescent population, social overload and information overload did not prove to be considerable technostress creators (Lutz et al. 2014). However, more than a third of the study participants perceived that they spend too much time on social networks (Lutz et al. 2014). Additionally, online communication load and multitasking behavior have been positively associated with perceived stress; age seems to moderate these effects (Reinecke et al. 2017).

[3] Large parts of this paragraph, the following table, and the following text until the end of the subsection are identical to the author’s own work published as Schmidt et al. (2021).

Technostress creator	Definition	Root concepts in literature
Overload	Overload represents all factors related to ICT that overextend the user through the number of ICT tasks or external demands delivered through ICT.	• Techno-overload (Ragu-Nathan et al. 2008) • Work-overload (Ayyagari et al. 2011) • Social overload (Lim and Choi 2017; Maier et al. 2012) • Smothering (Weinstein and Selman 2016a)
Invasion	Invasion represents all factors in which ICT causes or facilitates a conflict of interests between the digital and the offline world and, thus, interferes with the desired shaping of a domain of life independent of ICT.	• Techno-invasion (Ragu-Nathan et al. 2008) • Work-home conflict (Ayyagari et al. 2011) • Invasion (Maier et al. 2012)
Complexity	Complexity represents all factors of ICT that overextend users through insufficient skills or lacking knowledge for using ICT. Therefore, it forces users to spend time and effort on counterbalancing this mismatch of skills or knowledge and demands.	• Techno-complexity (Ragu-Nathan et al. 2008) • Complexity (Maier et al. 2012)
Uncertainty	Uncertainty represents all factors of ICT that create the demand for constant learning and educating oneself to keep up with the constant changes and updates of ICT.	• Techno-uncertainty (Ragu-Nathan et al. 2008) • Uncertainty (Maier et al. 2012)
Insecurity	Insecurity represents all factors of ICT that threaten an individual's perspectives for the future, particularly regarding job opportunities and the fear of becoming obsolete.	• Techno-insecurity (Ragu-Nathan et al. 2008) • Job Insecurity (Ayyagari et al. 2011)
Unreliability	Unreliability represents all factors of ICT that burden the user in the handling of ICT due to unforeseen errors (e.g., system crash, long loading times).	• Techno-unreliability (Ayyagari et al. 2011; Fischer and Riedl 2015)
Social Pressure	Social pressure represents all factors in which individuals perceive demands by their social environment to use ICT in a certain way or acquire a specific behavior.	• Pressure to comply (Weinstein and Selman 2016a) • Social Influence (Maier et al. 2012)
Disclosure	Disclosure represents all factors that cause individuals to feel fear of disclosing personal information via ICT, for example, due to unclear privacy settings or a lack of transparency on the processing of data.	• Privacy concerns (Lim and Choi 2017) • Disclosure (Maier et al. 2012) • Invasion of privacy (Ayyagari et al. 2011)

Table 4: List of Eight Technostress Creators Aggregated from the Literature

Technostress research focusing on private ICT use has also produced evidence for the existence of further technostress creators. Adolescents reportedly perceive exceptionally high demands from social pressure, privacy intrusions, and personal attacks (Weinstein et al. 2016; Weinstein and Selman 2016a). This finding is consistent with other studies indicating that individuals often feel socially pressured to use a specific ICT (Maier et al. 2012) and fear the invasion of their privacy via privately used ICTs (Ayyagari et al. 2011; Lim and Choi 2017; Maier et al. 2012). The literature also discusses cyberbullying and, in particular, ICT-facilitated personal attacks as technostress creators (Weinstein and Selman 2016a). However, since we perceive that in this case it is not ICT's techno-environmental conditions that create a demand but the person using ICT with the intention to harm another person, we exclude this perspective. Combining technostress research from organizational and private ICT use, literature holds a rich list of technostress creators (Table 4).

Although coping with digital stress is not conceptually different from coping with stress in general, a deeper understanding of the causes of digital stress yield various coping responses that specifically target digital stress. Existing studies on technostress coping verify that individuals use combinations of problem-focused and emotion-focused coping strategies in stressful situations. When facing significant ICT events, individuals can pursue four adaptation strategies mixing problem- and emotion-focused coping (Beaudry and Pinsonneault 2005), and emotions can influence the selection of these strategies (Stein et al. 2015). Efforts to mitigate the adverse outcomes of technostress from private ICT use can be divided into five technostress interventions (2017): Both the *modification of ICT features* and the *modification of ICT use routines* target the technostress creator and attempt to reduce its effect in the long run. The *modification of personal reactions to ICT stressors* facilitates toleration of the technostress creator by improving the individual's emotional handling. In contrast, *temporary disengagement from ICT* and *online and offline venting* form the action field "recovery from strain" and can help temporarily reduce the aftermath (Salo et al. 2017). Similar to these interventions, three types of control have been linked to technostress mitigation (Galluch et al. 2015). Exerting *method control* and *resource control* are coping behaviors in which individuals change their way of using ICT (method control) or avoid the stressful ICT environment (resource control). In contrast, *timing control* sets in earlier in the transactional process and enables individuals to influence when the demanding situation occurs (Galluch et al. 2015). Recent studies investigating specific coping responses confirmed that individuals *temporarily discontinue social media use* at high technostress levels (Maier et al. 2015b) or *distract* *themselves*, often even on the same social network that created the technostress (Tarafdar et al. 2020). Likewise, individuals that have to deal with complex and demanding IT security requirements tend to *morally disengage* from the requirements (D'Arcy et al. 2014). A rather radical approach to technostress coping gaining increasing popularity in combatting digital overload is ‘digital detox’ (Sutton 2017), the *temporary abstinence from ICT*. However, few publications have applied a broader view of what specific coping responses individuals activate to cope with technostress, indicating that research on technostress coping is still in its early stages. Various scholars have come to a similar conclusion and demand additional research efforts to understand better how individuals can cope with the specific demands of technostress (Tarafdar et al. 2019) or call specifically for a structured view on coping to promote greater understanding (Weinert 2018).

This section conveyed a common understanding of stress, digital stress, and coping as prerequisites for an intensified investigation of adolescents’ coping with digital stress (Chapter 4), the mobile assessment of stress (sections 5.1 and 5.2), and the design of a mobile stress coping assistant (section 5.3). To investigate these phenomena, the dissertation employs a wide range of different research methods. The next section gives a short overview of this methodological diversity.

2.4. Research Methods Used in this Dissertation

In IS research, two research paradigms are paramount: behavioral science and design science (Hevner et al. 2004; March and Smith 1995). In this dichotomy, the behavioral science paradigm targets to understand the world how it is, whereas the design science paradigm strives to create socio-technical artifacts that serve human purposes, thus, changing the world (March and Smith 1995). The two paradigms are not entirely independent perspectives but influence and complement each other in an iterating temporal order (Hevner et al. 2004). In these iterations, behavioral science research takes a retrospective view to examine and theorize existing and observable phenomena. In contrast, building on these theories, design science research takes a prospective view to solve the problems of today and shape the future. Comprehending IS research as the analysis of socio-technical systems, behavioral science focuses on examining how the social component behaves depending on the technical component, while design science targets the creation and evaluation of technical components with respect to social and socio-technical phenomena.

IS research creates both practical and scientific impacts (Baskerville et al. 2018; Hevner 2021). The practical impact is achieved when the results of the research solve a practical problem (Baskerville et al. 2018). Scientific impact is generally judged according to its contribution in terms of newly created knowledge (Hevner 2021). Both behavioral and design science research create new knowledge: behavioral science delivers descriptive knowledge; design science develops prescriptive knowledge (Gregor and Hevner 2013; March and Smith 1995). Descriptive knowledge (or Ω knowledge) targets an understanding of "what is." It comprises knowledge on natural, artificial, and human phenomena as well as theories on underlying patterns and laws. Behavioral science contributes to the Ω knowledge base by delivering generalized descriptive knowledge relating to the analysis, explanation, and prediction of the behavior of humans interacting with information technology (Gregor 2006). Prescriptive knowledge (or λ knowledge) provides answers to "how to" questions, specifically regarding the design of artifacts. The λ knowledge base contains two types of knowledge: *solution design entities* and *solution design theories* (vom Brocke et al. 2020b). Solution design entities deliver prescriptive knowledge in the form of tangible artifacts solving a defined problem. March and Smith (1995) describe four types of artifacts as design science research outputs: *constructs*, *models*, *methods*, and *instantiations*. Solution design theories comprise generalized prescriptive knowledge in the form of growing design theories on the actions, design processes, and implementations of solutions to a defined problem (Gregor and Jones 2007). Theoretical contributions of design science may range at different levels (Gregor and Hevner 2013). The lowest level of contribution refers to instantiations (as one of the artifact types) that solve a defined problem in a defined context without further abstraction or theorization. A medium level of contribution is reached when the presented knowledge includes some abstraction to a broader context as present, for example, in the case of the other artifact types (constructs, models, and methods) or design principles. Lastly, the highest level of contribution is achieved when a well-developed design theory is presented (Gregor and Jones 2007).

All IS research activities interact with the three knowledge bases introduced in section 2.4 (Ω knowledge, λ design theory, and λ design entities) (vom Brocke et al. 2020b). Therefore, vom Brocke et al. (2020b) distinguish six modes of how a research activity interacts with the knowledge bases. A research activity typically takes on multiple modes because it draws extant knowledge from one or more knowledge bases to inform the research and contributes newly created knowledge from the research activity to one or more knowledge bases. For each of the three knowledge bases, two modes of interaction exist: one for consuming knowledge and a second for producing knowledge (Table 5). Modes 1 and 2 interact with the Ω knowledge base. Mode 1 draws from the descriptive knowledge on natural and social phenomena to inform the research activity; mode 2 contributes to descriptive knowledge by feeding back newly gained insights regarding such phenomena. Modes 3 and 4 interact with the design theory knowledge base. Again, mode 3 draws from prescriptive knowledge on the design of solutions to inform the design and development of related design entities, whereas mode 4 contributes newly gained abstract design knowledge (e.g., design principles or theories) to the design theory knowledge base. Lastly, modes 5 and 6 interact with the design entity knowledge base, whereby mode 5 informs the research activity based on existing knowledge on the design of related entities, and mode 6 expands the design entity knowledge base contributing further design entity knowledge. Most research activities apply two or more modes because they build on existing knowledge and produce new knowledge.

Mode	Knowledge base	Description
1	Ω knowledge	Inform with descriptive knowledge on natural and social phenomena
2		Contribute new knowledge on natural and social phenomena
3	λ design theory knowledge	Inform with generalized prescriptive knowledge on solution design
4		Contribute new generalized knowledge on how to design solutions
5	λ design entity knowledge	Inform with entity-level prescriptive knowledge on solution design
6		Contribute new entity-level knowledge on how to design solutions

Table 5: Modes of Interaction with the Knowledge Bases

To address the manifold goals of behavioral and design science, IS research employs a wide variety of different research methods (Palvia et al. 2004; Palvia et al. 2015; Palvia et al. 2017) that can be classified into two overarching research methodologies: *qualitative research* and *quantitative research*. Qualitative research methods target the collection and contentwise analysis of qualitative data (e.g., narratives, observations) to hypothesize, interpret, and understand why something is the way it is (Kaplan and Maxwell 2005). Exemplary methods are workshops, interviews, literature analysis, and prototyping. Quantitative research methods involve the collection and (descriptive and inferential) statistical analysis of quantitative data (e.g., measurements, survey data, trace data) to substantiate existing hypotheses on natural and social phenomena (Bhattacherjee 2012). Examples include survey research, network analysis, laboratory experiments, and field studies (Palvia et al. 2004).

Besides quantitative and qualitative research, another methodological approach is enjoying increasing popularity in IS research. Also considered as a third methodology, mixed-methods research combines quantitative and qualitative research methods in one study (Venkatesh et al.

2013; Venkatesh et al. 2016). Unlike multi-method research (Mingers 2001), which refers to the combination of multiple methods from whatever methodological set, mixed-methods research always requires the combination of methods from different methodologies. Various benefits are associated with mixed-methods research. Combining qualitative and quantitative data collection and analysis, for example, enables the obtainment of complementary views on the same phenomenon or allows a research design where one study builds on the results of another (e.g., qualitative interviews pursuing the goal to interpret quantitative findings).

Striving for a broad investigation of digitalization's effects on individuals and technology's potential to promote positive outcomes, the dissertation at hand combines both behavioral science and design science research. In particular, Chapters 3 and 4 engage in behavioral science to produce descriptive knowledge on the behavior and consequences associated with individuals' DTM use, whereas Chapter 5 takes a design science perspective to create prescriptive knowledge on the design of stress coping assistants. The research activities employ research methods from all three methodological approaches. Specifically, Chapter 3 uses a field experiment (section 3.2) and mixed-methods research combining a network analysis based on trace data as well as interviews (section 3.1) to take a behavioral perspective on individuals' DTM use. Chapter 4 applies a mixed-methods approach combining workshops and a survey to analyze individuals' potential ways for reducing adverse consequences of their DTM use. Chapter 5 employs methods such as prototyping, field studies (sections 5.1 and 5.2), and a literature analysis (sections 5.2 and 5.3) to produce prescriptive knowledge describing how to design individual information systems assisting individuals in managing stress.

Building on this theoretical and methodological background, the following chapters present several research activities contributing to a deeper understanding of digitalization's effects on individuals. As a starting point, Chapter 3 analyzes individuals' behavior related to their DTM use.

3. Analyzing DTM Users' Behavior

The study of individuals' roles in socio-technical information systems involves three complementary perspectives: the analysis of individuals' *behavior* when interacting with DTM, the analysis of *consequences* arising from this behavior, and the *design* of new DTM addressing adverse consequences or problems of DTM use (Matt et al. 2019). The analysis of behavior "aims at an understanding of why and how individuals behave in certain ways and how this behavior can be influenced" (Matt et al. 2019, p. 317). Understanding these behavioral aspects sets the ground for further analysis and design of socio-technical information systems. Therefore, this chapter focuses on examining individuals' interactions with DTM and comprises two studies addressing different aspects of individuals' behavior. The first study (presented in section 3.1) investigates how users interact with each other across different channels (email communication and document collaboration) of a digital workplace suite. It yields eight roles users can take on depending on patterns in their communication and collaboration behavior and delivers qualitative rationales for this behavior. The second study (presented in section 3.2) evaluates how users change their venting behavior as a response to real-time feedback on indoor environmental quality. Thereby, the first study contributes to the first aspect (how and why individuals behave in a certain way) of the analysis of individual behavior, whereas the second study addresses the second aspect (how can this behavior be influenced). Major parts of Chapter 3 conform with Frank et al. (2017) and Bitomsky et al. (2020).

3.1. How DTM Users Behave and Interact at the Digital Workplace

The tertiary and quaternary (knowledge-intense) sectors of the economy have long been on the rise, and with it, the number of knowledge-intense jobs (Kenessey 1987). Many jobs in modern organizations, especially in the western world, require extensive amounts of knowledge work (Kane et al. 2012). In recent years, digitalization has brought forward many software tools to support communication and collaboration between knowledge workers. This development has led the digital workplace to grow continuously, particularly with new additions such as social collaboration platforms, enterprise social networks (ESN), or new communication tools like instant messaging (Gotta et al. 2015). Consequently, these market trends have prompted the development of new comprehensive software solutions (Gotta et al. 2015; Pawlowski et al. 2014). These tools have introduced many new functionalities to the digital workplace with goals such as increasing knowledge distribution beyond formal communication lines (Alavi and Leidner 2001), mediating communication and collaboration in distributed work environments (Seebach et al. 2011), helping blur organizational boundaries (Pawlowski et al. 2014), and ultimately increasing the productivity of knowledge workers (Kane et al. 2012; Köffer 2015). While companies are implementing these software solutions with great expectations, researchers and practitioners often report that adoption, usage, and impact are not yet fully understood (e.g., Berger et al. 2014; Herzog et al. 2015; Kiron et al. 2013; Kügler et al. 2012). Existing academic literature found that *one size fits* all solutions are inappropriate to address the heterogeneous job requirements and user behaviors of the digital workplace (Köffer 2015; Maruping and Magni 2015). Therefore, there is growing interest in evaluating social software initiatives in order to understand (1) why some users are adopting communication and collaboration tools and others are not, (2) which features are used by different user groups, and (3) which users create and distribute information within the organization. As a first step to better understand this heterogeneous usage behavior of knowledge workers within the digital workplace, an integrated analysis of both communication and collaboration technology is vital. While several studies exist which have brought forward first contributions regarding this issue, researchers frequently note that for privacy reasons, findings based on real-world data are scarce (e.g., Pawlowski et al. 2014; Wang and Noe 2010).

Therefore, the aim of this section is to derive a user typology from the informal social structure of a digital communication and collaboration environment in an organization in order to understand the heterogeneous user behavior as well as the emergent roles that knowledge workers take on and to investigate why they do so. The latter is necessary to draw specific inferences regarding theory and practice. To approach this goal, we conduct a mixed-methods study (Venkatesh et al. 2013): We start by deriving the social structure of an organization that provides knowledge-intense services from a digital trace data set, that is, data on user activity recorded by an information system (Howison et al. 2011). We do so with the tools of social network analysis (SNA) which serves as the basis of all further analyses. Subsequently, we use cluster analysis to explore various interaction types regarding the heterogeneous behavior of users. We then evaluate explanatory variables from metadata about the users through statistical testing in order to detect covariates of cluster membership. Lastly, we conduct semi-structured interviews with a theoretical sample of users informed by our previous findings to verify and better interpret our empirical results.

This study provides the following contributions: First, we identify eight distinct user roles of the digital workplace for knowledge workers from our real-world data set and explain their characteristics. Second, we find that several of the identified user roles show a strong relationship with the organizational hierarchy. Third, we categorize multiple other user roles as task-specific and report insights about them derived from the user interviews. This suggests that knowledge-sharing can be an in-role behavior for certain types of employees (Wang and Noe 2010). Fourth, we discuss how the identified user roles relate to the existing scientific body of knowledge, such as the organizational knowledge creation theory (Nonaka et al. 2006). Fifth, we discuss practical implications for the digital workplace that have previously been derived from the literature and discuss how our approach can help with addressing them.

Section 3.1 is structured as follows: The first subsection gives an overview of the elements of a digital workplace for knowledge workers and reviews the existing literature regarding user roles of knowledge workers. Subsequently, our mixed-methods approach and its components are explained. The third subsection contains the study's results. Next, we discuss the contributions derived from these results. Lastly, the fourth and fifth subsections assess our study critically regarding its limitations and conclude.

Problem Context and Literature Review

Knowledge Creation and Social Structures

According to the knowledge-based theory of the firm, knowledge is the primary resource of an organization (Grant 1996) and a superior knowledge base increases the value of an organization and its performance (Kogut 2000). Yet, despite the importance of knowledge, organizations often do not know what they know because their body of knowledge is comprised of the knowledge of individual employees as well as shared knowledge resulting from social interactions within the organization (Alavi and Leidner 2001). The fact that knowledge is mostly owned by employees places great emphasis on knowledge application and the role of the individual (Grant 1996). For knowledge workers, it is critical to know how and from whom to obtain the valuable information required to do their jobs (Cross et al. 2002). Congruent with that, a trend towards networked organizations and an emphasis on the social networks of employees is noticeable. The social interactions inherent in such networks are a manifestation of the structural dimension of social capital and are related to the extent of resource exchange within an organization (Tsai and Ghoshal 1998). It is well studied that social contacts help the members of intrafirm networks to maintain and extend their social capital within the organization (Steinfield et al. 2008). Communication and collaboration tools of the digital workplace can foster interactions, in particular between employees who are on different hierarchical levels (Behrendt et al. 2015) or who have no formal social relations with one another (Faraj et al. 2011; Kane et al. 2014). This, in turn, helps employees increase their access to the network and to gain social capital. Therefore, and to study organizational networks, an investigation of the implicit social structure that emerges from those interactions between the users of the digital workplace seems promising. While this is an important step towards understanding an organization's knowledge capability, little empirical research exists in that area (Richter et al. 2010). In relation to the implicit social structure, the existence of emergent roles is a particularly interesting topic in order to improve the understanding of user behavior. Emergent roles are roles that users take on implicitly and as a result of their interactions with others. In self-organizing collaboration communities such as Wikipedia, emergent roles are a cornerstone of the knowledge-creation process (Arazy et al. 2016). However, it remains unclear whether these emergent roles can also be observed for organizational settings.

The Digital Workplace for Knowledge Workers

Many jobs in modern organizations require extensive amounts of knowledge work (Kane et al. 2012). Thus, we are particularly interested in the digital workplace of the so-called knowledge workers. Knowledge workers are characterized as employees who "think for a living" (Davenport 2005, p. 3) and turn "complex information […] into knowledge" (Davenport 2005, p. 3). Davenport further sharpens the definition of knowledge workers as people that "have high degrees of expertise, education or experience, and the primary purpose of their jobs involves the creation, distribution, or application of knowledge" (Davenport 2005, p. 10). Köffer (2015, p. 2) introduced the digital workplace based on C. Tubb as "the collection of all digital tools provided by an organization to allow employees to do their jobs." As a first step to investigating the digital workplace for knowledge workers, it is important to understand and define the different software tools available to them. Generally speaking, there are software tools that are driven by structured and reproducible business processes rather than human interactions (van der Aalst et al. 2011), and those which foster open digital interactions between employees (Wang and Noe 2010). Examples of process-driven tools are enterprise resource planning or workflow management systems. These systems are not well-suited for the identification of an implicit social structure between employees because they follow pre-defined processes and often do not leave room for spontaneous personal interactions. Without the set perimeters of pre-defined business processes, however, an implicit social structure can emerge freely. We classify such software tools congruently with McAfee (2006) as communication channels and collaboration platforms. Communication channels include peer-to-peer communication tools, such as email or instant messaging, and cannot be accessed or searched by others (McAfee 2006). Collaboration platforms, such as content management systems, wikis, and blogs, by comparison, are accessible to many or all employees within the organization, and the knowledge stored in them is persistent (McAfee 2006). Both of those systems foster digital interactions between employees and therefore represent how people go about their daily business and whom they interact with digitally.

Related Work on User Roles

Recently, the existence and formation of emergent roles of knowledge workers have caught the interest of researchers. Multiple current studies have identified communication and collaboration use cases, including *Broadcasting, Dialog, Collaboration, Knowledge Management,* and *Sociability* (Schlagwein and Hu 2017; Schubert and Glitsch 2016). While these use cases provide a detailed outline of the functionality and capabilities of such a software environment, the authors do not attribute the use cases to specific user roles. Regarding email communication, there are a number of studies that have looked into network structures (e.g., Bird et al. 2006; Kane et al. 2012; van Alstyne and Zhang 2003), but surprisingly little research has addressed user roles. Among the notable exceptions are Alavi and Leidner (2001), who defined that in a digital environment, knowledge flows from a *Provider* to a *Seeker*, and that balancing the two is desirable. Muller et al. (2010) used real-world data to investigate the consuming behaviors of *Uploaders, Contributors*, and *Lurkers* within an enterprise file-sharing system. Reinhardt et al. (2011) created a general typology of knowledge worker roles based on a literature review. Subsequently, they verified the existence of *Controllers, Helpers, Learners, Linkers, Networkers, Organizers, Retrievers, Sharers, Solvers,* and *Trackers* through a laboratory task execution study. Their article provides a comprehensive overview of knowledge worker roles and their behaviors but lacks validation based on real-world data. In contrast to that, other authors have looked at real-world data of ESN to investigate the influence of formal hierarchy on user behavior (Behrendt et al. 2015; Riemer et al. 2015). Behrendt et al. (2015) found that in ESN, the hierarchy seems to have an influence on user behavior. Riemer et al. (2015), on the other hand, found that while hierarchy has a low influence on the likelihood of responses from the network, the users' own contributions are far more important. Those findings further substantiate the relevance of informal social structures in the context of ESN.

However, it remains unclear how significant the influence of formal hierarchy on emergent roles is. A study by Arazy et al. (2016) employed an SNA to identify seven emergent roles within the self-organizing collaboration platform Wikipedia. In their study, they found *All-round Contributors, Quick-and-Dirty Editors, Copy Editors, Content Shapers, Layout Shapers, Watchdogs,* and *Vandals.* A similar exploratory study by Füller et al. (2014) investigates the heterogeneous user behavior and the social structure of a collaborative open-innovation-contest community based on real-world data. In their study, they found six distinct user roles*: Socializers, (active and passive) Idea-Generators, Masters, Efficient Contributors,* and *Passive Commentators.* While their research approach is conducive to our goal of identifying user roles in a digital workplace, it is questionable whether their results can be directly transferred to the organizational context.

In summation, several researchers have previously dealt with user roles in the context of digital communication or collaboration, both within and outside of organizations. Their approaches cover a number of different software systems and reveal a number of domain-specific emergent roles. However, those studies have yet to combine both the communication and collaboration structures of a digital workplace. Additionally, to the best of our knowledge, an area that has yet to be addressed is the investigation into user behaviors in conjunction with reasons explaining why users behave the way they do or perform a certain informal role – especially in the presence of formal roles.

Empirical Study

To address the identified research gap, we use a mixed-methods approach (Venkatesh et al. 2013), which combines aspects of previous studies by identifying user roles in an exploratory fashion, analyzing potential influencing factors quantitatively, and interviewing users qualitatively to better understand the reasons for why employees act the way they do.

Research Setting and Data Set

Our exploratory study is based on digital trace data from a service organization that provides knowledge-intense services to corporate and individual customers. This organization is well-suited for this study for multiple reasons. First, it has two different locations with distributed teams consisting of employees from both locations. Therefore, it relies heavily on a distributed and digitally enabled work environment. Second, the organization uses the standard software Microsoft Office 365 with its social collaboration component SharePoint and the communication system Exchange. In that regard, the platform resembles a significant part of the communication and collaboration technology used in many companies today (Gotta et al. 2015). Third, the organization almost exclusively employs knowledge workers. While this organization is well-suited for our research goal, we do acknowledge that studying a single organization bears limitations on the inferences that can be drawn from our study. Further, we acknowledge the limitation of only analyzing the most dominant digital collaboration and communication system in the organization while, for example, omitting interactions through phone calls or personal contact for lack of trace data.

The organization has multiple specialized departments which are responsible for the provision of the organization's external service offerings and support functions that provide internal shared services, such as Finance or Human Resources (HR), to all departments. Each full-time employee is a member of exactly one department and one or multiple support functions. For the purpose of our research, we were provided with digital trace data for a period of six weeks across the months of March to May 2016. At the time, the organization had a total of 146 registered employees who were users of the digital workplace. Amongst the 146 users were 6 Heads of Departments, 6 Heads of Support Functions, 8 Assistants to the Heads of Departments, 35 Full-time Employees, and 91 Part-time Employees. Part-time employees have variable working hours, generally with about 10 hours per week. Almost all users can be counted towards the knowledge worker category, as they mainly have high degrees of education and work experience in professions like management, business, and financial services, or computer sciences (Davenport 2005).

For our study, the digital trace data was pseudonymized by the organization's system administrator to address privacy concerns (e.g., Herzog et al. 2015; Köffer 2015; Pawlowski et al. 2014; Wang and Noe 2010). This ensures the identification of communication and collaboration patterns but prevents the researchers from knowing about the content or from identifying individual employees (van Alstyne and Zhang 2003). Both the Exchange and SharePoint logs contain only internal communication and collaboration but do not include recipients or users outside of the organization. To identify characteristics of users, who perform a certain role, we were provided with the user-specific binary attributes *gender*, *site* (differentiating between the company's two sites), and *length of employment* (split into "long" and "short" according to the median), as well as the *position in the organizational hierarchy* (distinguishing between five hierarchical levels). The selection of the attributes and their granularity was chosen in such a way that each combination of attributes matched multiple (or no) employees of the organization, but never a single one.

Social Network Analysis and Interaction Patterns

We use the tools of SNA as a basis to study the heterogeneous user behaviors and derive different user roles from the resulting social structure. SNA is ideally suited to study the actors of a given social system (Wasserman and Faust 1999) and has been used in social sciences for many decades (Borgatti et al. 2009). With metrics drawn from the social structure, actors can be distinguished, potentially resulting in new insights into user roles (Arazy et al. 2016; Füller et al. 2014). The foundation of many SNA concepts, such as *centrality* and other actor-related measures, is graph theory (e.g., Füller et al. 2014; Wasserman and Faust 1999). The relational structure of a social system consists of patterns of relationships among the actors of the system. Network data is fundamentally dyadic, meaning that ties are observed for a set of two actors at a time (Borgatti and Foster 2003). The sum of those actors and the ties amongst them form a social network (Wasserman and Faust 1999). Such an approach focuses on the patterns of interconnection but tends to neglect the content of the network ties between the actors (Borgatti et al. 2009). It is based on the idea that an actor's position in a network influences their opportunities and constraints (Kane et al. 2014). This approach is conducive to our pseudonymized data set, which contains communication and collaboration patterns but not their contents.

SNA typically considers one or more of the following basic tie types: proximity (co-membership in groups, such as departments), relations (social relationships, such as friendship), interactions (discrete exchanges between nodes, such as a conversation), and flows (tangible or intangible material that moves from one node to another, such as information) (Borgatti et al. 2009; Kane et al. 2014). While flows are important because "information flows drive knowledge transfer in organizations" (Alavi and Leidner 2001, p. 119), they are often difficult to measure. Consequently, and congruent with previous IS research regarding IT platforms and channels, we focus primarily on interactions (Kane et al. 2014). To understand the differences between our two IT systems, it is important to differentiate between the channel, which "pushes" information, and the platform, which requires users to "pull" information. For the push-medium email communication (i.e., Exchange), the sender initiates an interaction by sending an email. For the pull-medium content collaboration (i.e., SharePoint), however, the sender provides content to the IT system and the retriever accesses this content, resulting in an interaction.

The application of SNA in IS has long focused on single links, which contrasts multiplex approaches common in the social sciences (Howison et al. 2011). In our case, interactions can cover several distinct forms of communication or collaboration between two users. We define the following four possible dyadic interaction patterns that can be observed within the given data set, as presented in Figure 7:

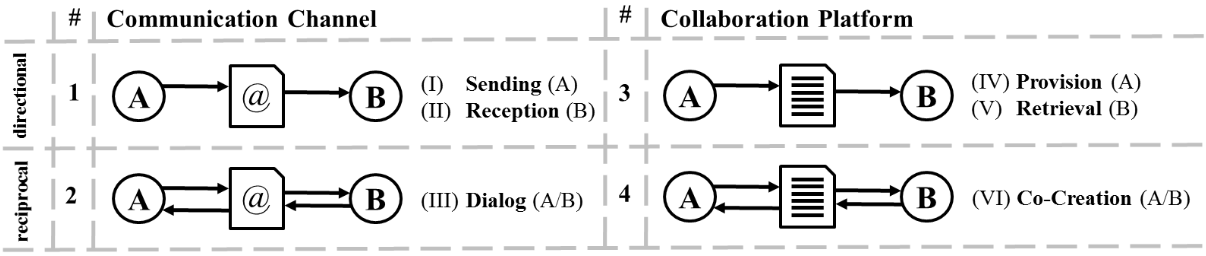


Figure 7: Interaction Patterns

Content co-creation and email dialog, as defined in this section, are by definition reciprocal and thus do not have a direction. The other two interaction types are directional, however. The strength of a tie is determined by the frequency or depth of a connection, which can be determined by interaction data (Kane et al. 2014). In our study, the strength of an interaction tie is defined by the number of different files and email subjects that two actors interact on.

In order for the observed interaction types to be transferred into input parameters for our cluster analysis, measures of contribution for the individual users need to be defined. There are several actor-based (egocentric) structural features that can be measured for a network which are commonly referred to as the centrality of an actor (Füller et al. 2014; Kane et al. 2014; Wasserman and Faust 1999). Those concepts are related to the importance, prominence, and visibility of an actor within a network. For the purpose of our study, we focus on degree centrality as a measure of activity (Wasserman and Faust 1999) and for greater access to network flows, such as information disseminated through interactions (Kane et al. 2014).

Analysis and Results

User Typology

To construct a social network from the log files, the defined interaction patterns were first mined from our digital trace data set. We find that the average number of colleagues a user is connected to through content collaboration is substantially lower than via email communication (10.6 and 8.9 for collaboration vs. 55.7 and 78.3 for communication). A deeper examination of the ties' intensity, which refers to the number of files or email subjects they have interacted on, reveals that users, who are connected, have on average approximately four bilateral and five unilateral communication ties (i.e., communicate on four email subjects in a discussion and on five subjects one-sidedly), but only three collaboration ties (i.e., collaborate on three files). In the social network, the overall number of interactions (weighted with their intensity) for the two directions of unilateral network ties (email sending/reception and content provision/retrieval, respectively) is identical, and therefore, the means are too. Median and standard deviation (SD) can differ depending on the directionality. For example, a single user can send emails to multiple recipients, which results in a more even distribution for email reception than for email sending. The mean number of sending and reception ties, however, stays the same. The descriptive statistics on the frequency of interactions (Table 6) show that more users are connected through communication ties (means of 271 and 297.4) than through collaboration ties (means of 33.2 and 23.2). The heterogeneous standard deviations substantiate the assumption that users behave differently from one another. A large standard deviation for the email sending measure (327.5 compared to 185.2 for email reception), for example, suggests that a limited number of users are responsible for the majority of unilateral communication. However, due to the skewness of some of the data, the standard deviation has to be taken with a grain of salt.

	Variable	Mean	Median	SD	Skewness
I	Email Sending	271.0	170.0	327.5	3.70
II	Email Reception	271.0	212.0	185.2	1.35
III	Email Dialog	297.4	226.5	238.2	1.87
IV	Content Provision	33.2	18.5	47.3	3.41
V	Content Retrieval	33.2	22.5	43.2	4.17
VI	Content Co-Creation	23.2	11.0	29.3	2.27

Note: Observations: n = 146, SD = standard deviation

Table 6: Descriptive Statistics on the Frequency of Interactions

We used the interaction types to capture each user's communication and collaboration behavior as input variables for an exploratory cluster analysis aimed at identifying the distinct user types inherent in the social structure of our network. To do that, we first checked if both the measures for the unweighted graph, which records whether or not any tie exists between two users as a binary measure, and the weighted graph, which includes the strength of every tie, present a potential source of heterogeneity. We found that the Spearman rank correlation coefficients between the unweighted and weighted means reside between 0.88 and 0.98, depending on the type of interaction. Therefore, we decided to only use the weighted graphs because they contain more information and their interpretation regarding the usage patterns is more straightforward, as it represents the extent to which the users use the interactions and not just the number of colleagues they are connected to.

For our cluster analysis, we used an agglomerative hierarchical procedure with the Ward.D2 minimum variance method and the Euclidian distance. Hierarchical clustering usually works well (Füller et al. 2014), is reproducible, and does not need the desired number of clusters, or their size, as an input parameter, which is conducive to our exploratory approach. Also, users that have been added to one cluster will remain in that cluster even if the cluster solution is changed, which helps with the process of determining the appropriate number of clusters. To eliminate outliers, we censored all values above the respective 98% quantiles.

"There is no universal definition for a good clustering size, [rather] the evaluation remains mostly in the eye of the beholder" (Bonner 1964; Rokach and Maimon 2005, p. 326). Several different stopping rules (Milligan and Cooper 1985) were employed but yielded inconclusive results. We found that for eight clusters, the results are well interpretable. A lower cluster size joined multiple clearly distinct user groups, whereas more clusters resulted in very small cluster sizes with clusters that may be regarded as outliers rather than distinct user groups.

From our cluster analysis, we conclude the following typology: of the eight distinct user types, there are three that use both the communication channel and the collaboration platform roughly to the same extent. These clusters are labeled *All-rounders* with *low*, *mid*, and *high activity*. Four of the clusters are labeled according to a peak in one or more of six clustering dimensions. Two user types with peaks in communication interactions (Email heavy-users and broadcasters) were observed and two user types with peaks in collaboration interactions (Content co-creators and providers). Lastly, a user group that remains largely passive on both systems was identified. An overview of all clusters is provided in Table 7.

A nine-cluster solution would have split Content Providers into two, creating a user group of two individuals that not only provide content but also heavily retrieve content. As mentioned above, this group was omitted for its small size and because the characteristic attributes of Content Providers are still present in this ninth cluster. This is apparent in the data as part of the relatively high standard deviation of 0.35 in Content Retrieval of the Content Providers. A seven-cluster solution, on the other hand, would have joined Content Co-Creators and All-rounders High-Activity that considerably differ in content co-creation and email dialog.

		Interaction Types											
		Communication Channel						Collaboration Platform					
		Reception		**Sending**		**Dialog**		**Retrieval**		**Provision**		**Co-Creation**	
User Role	#	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD
All-rounder High-A.	9	**0.67**	0.11	**0.58**	0.14	**0.78**	0.20	**0.61**	0.23	**0.44**	0.21	**0.52**	0.13
All-rounder Mid-A.	16	**0.55**	0.16	**0.36**	0.13	**0.42**	0.13	**0.26**	0.10	**0.22**	0.10	**0.35**	0.12
All-rounder Low-A.	33	**0.30**	0.13	**0.20**	0.10	**0.28**	0.12	**0.19**	0.16	**0.13**	0.09	**0.14**	0.10
Email Heavy-User	8	**0.86**	0.13	**0.75**	0.15	**0.75**	0.15	**0.20**	0.07	**0.12**	0.07	**0.32**	0.27
Email Broadcaster	7	**0.31**	0.15	**0.89**	0.12	**0.53**	0.17	**0.11**	0.08	**0.15**	0.11	**0.07**	0.06
Content Co-Creator	11	**0.56**	0.16	**0.50**	0.15	**0.44**	0.11	**0.55**	0.14	**0.51**	0.21	**0.80**	0.20
Content Provider	8	**0.29**	0.07	**0.20**	0.07	**0.25**	0.07	**0.47**	0.35	**0.77**	0.24	**0.32**	0.13
Passive User	54	**0.17**	0.07	**0.08**	0.07	**0.13**	0.05	**0.06**	0.05	**0.03**	0.04	**0.04**	0.04

Note: SD = standard deviation

Table 7: User Typology with Corresponding Means and Standard Deviations of the Different Interaction Types

The *All-rounder High-Activity* (6.16% of 146 users) is characterized by fairly high email interactions, which suggests that this user type communicates heavily in a digital way, especially through email dialogs. A mean of 0.78 for email dialogs states that, on average, this user type has 78% of the interactions of the most active user in the network. This user type is also fairly active on the collaboration platform (1^{st} to 3^{rd} highest, depending on the interaction type), where they provide and retrieve content, in addition to co-creating content with their colleagues.

The *All-rounder Mid-Activity* (10.96%) is less active than its high-activity equivalent. While their number of received emails is comparable to those of an All-rounder High-Activity, they engage significantly less in reciprocal communication, as measured by the number of email dialogs.

The *All-rounder Low-Activity* (22.60%) forms the second-largest cluster. This user type is considerably less active (2nd to 3rd last in all interaction types) than the formerly mentioned All-rounder types.

The *Email Heavy-User* (5.48%) engages much more heavily in email communication than in any collaborative activities. The peak in received emails is also substantial, which according to Wasserman and Faust (1994) is an indicator for a prestigious user. If this user type engages in any collaboration activity, it's mainly through the co-creation of content with other users. Very rarely does this user type provide content that other users access.

The *Email Broadcaster* (4.79%) has a strong peak in outgoing email communication (most), but receives comparably small amounts of emails. However, this user type also has a fairly large amount of email dialog interactions (3rd most), likely as a result of the high number of sent emails.

The *Content Co-Creator* (7.53%) uses the collaboration platform and the communication channel fairly heavily but has a substantial peak in content co-creation (most). This indicates that the user type collaborates heavily with other users in order to create tangible content.

The *Content Provider* (5.48%) is fairly active with regard to collaboration interactions and has a significant peak in content provision. This indicates that this user type creates tangible content that other users access frequently. The communication interactions, however, are sparse (2nd lowest) for this user type.

Finally, the *Passive User* group makes up for the majority of the users (36.99%). This user type has the lowest values across all interaction types and therefore does not participate particularly actively through digital communication or collaboration within the organization.

Covariates of Role Membership

To investigate the association between our categorical explanatory variables and the eight user types, we first examine the contingency tables illustrating the relative frequency distributions (Agresti 2007). We then apply a chi-squared-test for independence to determine whether there is a significant difference between the expected and observed frequencies. To deal with small cell values for rare user types, we simulate the associated p-values through a Monte Carlo Simulation (Hope 1968). First, we study the relationship between the identified user roles and the organizational hierarchy. Organizational hierarchy is a factor that has been mentioned frequently in the literature regarding user behavior in the context of digital communication (Behrendt et al. 2015; Riemer et al. 2015). We observe a strong relationship between the identified user roles and the position in the organizational hierarchy (Table 8). The association between the two variables is highly significant ($p<0.01$) with a chi-squared test statistic of $X^2 = 184.81$. We find that Heads of Departments and Heads of Support Functions tend to be heavy email users, as observed in 50% of the cases. These users communicate heavily via email but tend to use the collaboration platform to a substantially lesser extent. Assistants to a Head of the Department, conversely, mainly belong to the *All-rounder High-Activity* category. This user type is similarly involved in email communication than heavy email-users, but also engages heavily in collaborative activity, resulting in a more balanced usage of the collaboration platform and the communication channel. The full-time employees who do not hold a leadership role are widely spread across the different user types, with a peak at *Content Co-Creators* and A*ll-rounders of Low- and Mid-Activity*. This shows that in our study, regular full-time employees are generally less involved in email communication than their superiors. However, about one-third of the full-time employees are heavily involved in collaborative activities, in particular, content co-creation with other colleagues. This is an observation that will be subject to further qualitative investigation in the following subsection. Part-time employees are mostly *Passive Users*. This user type receives more emails than it sends and has a very low engagement on the collaboration platform. The rest of the part-time employees are mainly *All-rounders of Low-Activity*.

	Organizational Hierarchy					
User Role	**Head of Department**	**Head of Support F.**	**Assistant to H. of Dept.**	**Full-time Employee**	**Part-time Employee**	# of people
All-rounder High-Activity		17 %	63 %	9 %		9
All-rounder Mid-Activity	17 %	33 %	25 %	23 %	3 %	16
All-rounder Low-Activity	17 %			17 %	29 %	33
Email Heavy-User	50 %	50 %	13 %	3 %		8
Email Broadcaster	17 %			9 %	3 %	7
Content-Co-Creator				31 %		11
Content Provider				3 %	8 %	8
Passive User				6 %	57 %	54
# of people	6 (100 %)	6 (100 %)	8 (100 %)	35 (100 %)	91 (100 %)	146

Table 8: Contingency Table for User Role and Organizational Hierarchy

In general, the organizational hierarchy does not fully explain all user types, but the different hierarchical levels show (more or less) clear tendencies towards a specific user type. To get a better picture of the factors related to the cluster membership, we proceed to analyze three additional potential covariates. First, regarding the organization's two different *sites*, we find a significant difference in the expected frequencies across all roles ($p<0.10$). According to a column-wise chi-squared test for goodness-of-fit, this is mainly due to the clusters All-rounder High and Mid-Activity, as well as due to the Email Broadcaster and Content Provider. For All-rounders High-Activity, the cause may be a higher number of Assistants to Head of Departments that are located at site A - the organization's oldest branch. Broadcasting and Content Provision activities might possibly be related to a high number of shared services, which are located at site A. Second, we examine the association between *gender* and emergent roles and do not find significant differences across our clusters ($p=0.58$). Previous studies regarding knowledge management have found a significant influence of gender diversity on knowledge sharing (Wang and Noe 2010). Third, regarding the *length of employment*, we find a highly significant association ($p<0.01$). We observe that Email Heavy-Users and All-rounders of High and Mid-Activity are more likely to have been with the company for a long time, while passive users have been with the company for only a short time significantly more often. However, both of those observations are correlated with the organizational hierarchy, as superiors tend to have been a part of the organization for a longer period of time than part-time employees in this organization.

User Interviews

We follow up on the quantitative results through qualitative user interviews as part of our mixed-method approach to qualitatively confirm the quantitative results (Venkatesh et al. 2013). To do so, we conduct *semi-structured face-to-face interviews* with members of the organization (Myers and Newman 2007). The nine interviewees are selected based on *theoretical sampling* informed by the insights gained from our previous findings (Anderson 2010; Glaser and Strauss 1967). Because of the pseudonymized data, it is not possible to select interviewees based on their emergent roles. However, due to the strong correlation between the organizational hierarchy and the identified user types, we are able to use the users' organizational positions to determine appropriate interview partners. Therefore, we select three part-time employees (A, B, C), three full-time employees (D, E, F), an Assistant to a Head of Department (G), a Head of Support Function (H), and a Head of Department (I). Similar to Behrendt et al. (2015), who used a mixed-methods approach to investigate an ESN in a medical context, we defined the following two stages for the qualitative part of our study: Intended behavior and use cases of interaction types (Interview Stage 1), and addressing the findings of the quantitative analysis to allow for confirmation, rejection, and explanation (Interview Stage 2). All interviews were conducted, recorded, and transcribed by the authors of this study. The transcripts were then coded iteratively to identify categories of repeated answers that address the overarching questions of the two interview stages mentioned above.

Intended Behavior and Use Cases

In the first stage, we intend to learn more about why the interviewees use the communication channel and collaboration platform, respectively, and why they engage in the respective identified interaction types. In general, email communication is used for coordination, information sharing, or to document decisions in a written form, particularly with other employees who are not physically available. Email dialog is mainly used for coordination and status updates, while unanswered emails are for announcements, triggers, or simply to inform somebody about something – for example, through a copy of an email.

The collaboration platform, on the other hand, is used to co-create and archive knowledge, make content accessible to a larger audience, and look for and find information. For content co-creation, people frequently mentioned use-cases, which require intensive teamwork. In addition to co-creating content, they also mentioned receiving input or detailed in-text feedback through that kind of interaction. It was frequently mentioned that content stored on the platform is persistent, durable, and safe. Additionally, administrative tasks such as shared lists, instructions, and tutorials were mentioned. Content retrieval is used to access (or provide) input for knowledge creation, informational lists, meeting minutes, and other protocols. Overall, this shows that users are making conscious decisions about when they use which software. It also confirms that our defined interaction types are indeed recording heterogeneous behavior and that the patterns capture distinct information.

When asked about the most important influencing factors for why somebody would use communication channels or collaboration platforms more or less intensely, the interviewees almost unanimously confirmed the position in the hierarchy to be of relevance and also mentioned the nature of the individual tasks. Interviewee H stated: "You have to view it in the context of the task. [A part-time employee] has vastly different communication requirements than an Assistant to the Head of Department, who has to coordinate important strategic issues with multiple stakeholders". Experience with the software systems, as well as personal preference and IT skills, were also mentioned in this context.

Addressing the Quantitative Findings

In the second stage, we asked the interviewees to address our quantitative findings and to provide explanations as to why the observed patterns may exist. For that, they were shown versions of Figure 7, Table 7, and Table 8 before being asked questions such as: “We observed that Assistants to a Head of Department are more heavily involved in content collaboration than other employees. Judging from your experience and interaction with them, is this a plausible observation, and if so, why do you think they are?”

All but two *Passive Users* are part-time employees. Per our interviewees, part-time employees communicate and collaborate significantly less because they work fewer hours and have fewer tasks: “They have fewer duties that they need to communicate and collaborate on. Things like delegating, controlling, and guiding are mainly done through communication – and that’s not typically part of a part-time employee’s job description”, Interviewee H.

We identified three levels of *All-rounders* who use the two systems with rather similar intensity. Thus, we conclude that Mid-Activity All-rounders represent the average usage amongst employees who work full hours, while Low-Activity All-rounders use both systems to a lesser degree. High-Activity All-rounders are occupied by middle managers who depend on documenting decisions in a structured way: “Depending on the size of their department, they have to maintain a lot of lists to keep an overview of all the topics that they deal with. They also gather a lot of information from the entire organization and transform or condense it for their bosses”, Interviewee G. They also often organize meetings and bring decisions made by the participants into practice, which requires extensive amounts of communication: “It has got to do with our responsibilities. Management assistants are the binding element between their superiors and the other employees. They have to gather a lot of information, condense it, and pass it on. That happens mainly via email, as many employees are working on external projects during the week”, Interviewee H.

According to our interviewees, *Email Broadcasters* are (1) organizers of certain expert group meetings and other regular events, who ask for input from the participants, send agendas, and schedule meetings, or (2) the main secretary’s office, which often sends emails to multiple recipients to inform them about changes regarding meetings, updates about decisions, or forward emails that they receive centrally but for which they are not responsible, or (3) single-point-of-contacts: “I receive emails with some brief information from my boss, based on which

I write a proper email and communicate the matter to everybody else in the department," Interviewee B.

Email Heavy-Users communicate more than they collaborate with others. The high number of incoming emails indicates that these users are particularly prestigious (Wasserman and Faust 1994). First, managers "have exponentially more tasks" than employees on lower hierarchy levels. "It's a cascading effect. For every task, you receive status updates which accumulate accordingly", Interviewee E. They give input, set goals, and monitor progress but do not necessarily get involved operationally. Secondly, the reason why this communication is done via email was explained by a lack of in-person availability. "That's why they depend heavily on emails. Usually, they answer a bulk of emails in the evening", Interviewee G. Interviewee I added that he uses emails frequently because he "travels a lot and the integration of the email client works flawlessly on the smartphone."

Content providers are all located at site A where most shared services are situated. We, therefore, suggest that this user behavior is task-specific. According to our interviewees, there are employees who are responsible for creating and updating tutorials, descriptions, frequently asked questions, or templates. Frequently mentioned were the IT, Public Relations, and Finance departments. Given the fact that most Content Providers are part-time employees and that the information stored in the mentioned documents is rather broad, we conclude that Content Providers are employees who gather and document information, rather than necessarily creating it themselves in the first place. Another interesting finding from the self-assessment was that content provision was rated low across the board, which suggests that providers of content are often unaware of others using their work.

For *Content Co-Creators***,** extensive teamwork is an important factor. Interviewee F said: "that's again task-related. More time for projects, proposals, or evaluation reports means more collaboration with others." Some interviewees mentioned that teams that work in distributed environments, such as different internal locations or external projects, might engage more in content co-creation.

Meta-findings

To sum up our insights from the three parts of this study, we provide the following meta-inferences from integrating the qualitative and quantitative findings (Venkatesh et al. 2013). The results of the different parts of our study are presented in Table 9.

User Role	Profile	Most Common Hierarchical Position	Other important Attributes	Qualitative Insights
All-rounder High-Activity	Frequent email communication, especially dialog. Frequent content collaboration	Assistant to Head of Dept.	Long employment & Site A	Middle management; a broad portfolio of tasks; structured documentation; efficiency of coordinative tasks.
All-rounder Mid-Activity	Moderate email communication. Moderate to low content collaboration	All levels	Long employment	Average usage of channel and platform.
All-rounder Low-Activity	Moderate to low email communication. Low content collaboration.	Part- & Full-time Employee	-	Below average usage of channel and platform.
Email Heavy-User	Frequent email communication, especially reception. Low content collaboration.	Head of Support Function & Head of Department	Long employment	Limited in-person availability; lots of coordination, input, and feedback through cascading effects of responsibilities.
Email Broadcaster	Moderate email communication, but very frequent email sending. Low content collaboration.	Part- & Full-time Employee	Site A	Task-specific: scheduling of meetings; newsletters; single-point-of-contact in certain shared services, e.g., IT department, secretary's office.
Content Co-Creator	Moderate email communication. Frequent content collaboration, especially content co-creation.	Full-time Employee	-	Task-specific: when extensive teamwork is required and in distributed teams: e.g., research, written proposals, internal and external projects.
Content Provider	Low email communication. Frequent content collaboration, especially content provision.	Part-time Employee	Site A	Shared services and administrative tasks: e.g., instructions, tutorials, and templates in Finance, IT, HR departments.
Passive User	Very low email communication. Very low content collaboration.	Part-time Employee	Short employment	Fewer tasks & work hours; mainly operational tasks; more in-person contact through open-plan office, fewer meetings.

Table 9: Meta-Findings – User Roles with Quantitative and Qualitative Factors

We found that part-time employees use the communication channel and the collaboration platform less frequently than full-time employees. However, task-specific exceptions, such as Content Providers or Email Broadcasters, are possible. In the user role Content Provider, part-time employees do not necessarily create new knowledge but document existing tacit knowledge or merge dispersed knowledge to make it tangible. Full-time employees occupy many different user roles. The majority of them use both systems with relatively equal intensity and tend to be All-rounders of Low- or Mid-Activity. However, for task-specific reasons, about one-third of them are engaged in tacit knowledge creation with their co-workers and are therefore Content Co-Creators. All of the user roles observed for full-time employees communicate significantly less than the roles most frequently observed for top managers (Head of Support Function, Head of Department) and middle managers (Assistant to Head of Department). Assistants to the Heads of Departments are highly active on both systems and are thus High-Activity All-rounders. They have a broad portfolio of tasks where they are required to obtain information from employees and restructure or condense them to suit the needs of their superiors. In addition to that, they frequently organize meetings and take minutes to document decisions made by their superiors. Heads of Departments, just like Heads of Support Functions, are mainly using the communication channel and not the collaboration platform. Their job profile requires extensive amounts of coordination and communication because they are ultimately responsible for all tasks within their departments and are required to keep up with all developments, as well as to give high-level input or feedback where necessary. Due to their limited in-person availability, the communication is often asynchronous and, therefore, digital.

Several outliers that do not follow the observed correlations between user roles and organizational positions are also apparent. For users who communicate or collaborate less than the rest of their co-workers on the same hierarchical level, this could be for personal factors such as vacation time, which we did not include in the quantitative part of our study for privacy reasons. Particularly interesting, however, are users who communicate and collaborate more than their peers. For example, part-time employees who are Mid-Activity All-rounders or full-time employees who are High-Activity All-rounders. We suggest, and our interviews support, that these users might be so-called *hidden leaders*. Such employees use relationships and interactions with others to manifest their leadership and do not rely on a hierarchical position to influence others (Edinger and Sain 2014).

Discussion

Theoretical Implications

Several researchers have previously dealt with the roles of knowledge workers, different use cases of communication and collaboration software, and hierarchical differences in social software usage. However, the previous findings leave room for further contributions. This is due to several reasons: First, little research relies on real-world data. Second, the rare exceptions do not combine both collaboration and communication systems in an integrated way. Third, the mentioned studies rarely investigate exogenous covariates for specific user behavior. Our study identifies and analyzes eight heterogeneous user roles to address this gap.

Previous research regarding ESN has found relationships between the organizational hierarchy, on the one hand, and communication and knowledge sharing, on the other hand (Behrendt et al. 2015). Others, however, call for deemphasizing the role of hierarchy in knowledge sharing (Wang and Noe 2010). In our study, we find strong associations to the organizational structures for many user roles. However, for other roles, specific tasks that the users perform seem to be the distinguishing factor. For example, the user group identified as Content Providers has frequently been described in the literature as Providers or Sharers (Alavi and Leidner 2001; Reinhardt et al. 2011). According to several statements of the software environment's users in the qualitative part of our study, Content Providers are people whose jobs require them to gather information and create content that is frequently accessed by other users. This is congruent with Wang and Noe (2010), who state that knowledge sharing can be an in-role behavior for certain employees. The same applies to Email Broadcasters. Schlagwein and Hu (2017) observed broadcasting behavior in the context of ESN and directly compared it to email broadcasting. According to the authors, broadcast in general is primarily aimed at reaching many users with a preconceived message. Such messages usually contain formal rather than informal information when transmitted via email (Schlagwein and Hu 2017). Based on our user interviews, the respective user group is indeed tasked with the broadcasting of information, for example, in the form of internal newsletters. In addition to that, we learn from our interviews that the group might also be involved in the planning and scheduling of meetings, which according to Reinhardt et al. (2011) is the task of an Organizer. Due to the pseudonymized data set, we cannot conclusively say whether organizing is a relevant factor for the emergence of Email Broadcasters. For instance, according to our interviews, Assistants to the Heads of Departments are also frequently involved in such activities, but in addition to that, they also heavily participate in other interactions. Therefore, while we find users who perform tasks attributed to an Organizer, we cannot say with certainty whether some of them would form their own user group if the content of their interactions were considered.

A large part of the users in our study are all-rounders, which is congruent with a study by Arazy et al. (2016), who investigated emergent user roles in the open collaboration platform Wikipedia. For example, in our study, the majority of Assistants to the Heads of Departments – who are middle managers – are High-Activity All-rounders characterized by high levels of communication and collaboration activities. The organizational knowledge creation theory (Nonaka et al. 2006) can provide an explanation for this observation. It has, amongst other things, dealt with the role of leadership in knowledge management. According to Nonaka et al. (2006), top-level managers communicate and coordinate visions about knowledge throughout the organization. Congruent with that, we find that Heads of Departments and Support Functions – who are top managers – are heavily involved in email communication and not so much in collaborative activities such as content provision or co-creation. For reasons of cost and time, not all knowledge can be shared (Nonaka et al. 2006). This is particularly the case for people high up in the hierarchy whose time is particularly precious. According to our interviews, this might be a reason why Heads of Departments and Support Functions tend to create less tangible content through the collaboration platform and use asynchronous and verbal communication more frequently. Middle managers, on the other hand, bring the visions of top managers into concepts and facilitate organizational knowledge creation by synthesizing knowledge of front-line employees as well as of their top managers and help make it explicit (Nonaka et al. 2006). These users are described in our user interviews as employees who gather information and reshape it to suit the needs of their superiors. In that sense, their behavior also resembles that of Linkers who "mash up information from different sources to generate new information," as found in a study by Reinhardt et al. (2011).

Contrary to previous studies which hypothesized and found Retrievers, Learners, or Seekers (Alavi and Leidner 2001; Reinhardt et al. 2011), we do not find a user group that has peaks in content retrieval in our real-world data set. While many of the identified user types rely heavily on content retrieval, they also convert that information into tangible content to a similar extent. Because our study is based on social network data, we only consider content that was modified within the six-week observation period. It remains unclear whether the absence of Retrievers might be influenced by that restriction. However, it seems reasonable that employees do not look for information simply for the sake of knowing it, but that they do something with the obtained information. This then results in more balanced user types, which according to Alavi and Leidner (2001) is desirable, at least on an aggregated organizational level.

Several previous studies regarding digital social structures report about a dense network core and a large periphery of rather passive users (e.g., Füller et al. 2014; Muller et al. 2010). We, too, found a passive user type; however, we are uncertain whether this is due to the uncommon organizational structure with many part-time employees or if it is a phenomenon that can generally be observed for employees with operative tasks. Congruent with our observation and within a different organization, Behrendt et al. (2015) found that lower hierarchical levels are less active in ESN. In their study, the lowest hierarchical levels barely participate in ESN at all; average hierarchical levels have the most social relationships, middle managers communicate actively, and top managers reach many users at once. In our study, some part-time employees pointed out that their lack of digital communication and collaboration might be due to a higher level of personal interactions in their open-plan offices. However, the effect of such personal interactions on digital interactions is not considered in our quantitative analysis.

Lastly, we find several employees who do not fall into task-specific roles but also are not in the same cluster as their colleagues on the same hierarchical level. We consider these to be outliers that communicate and collaborate more than their peers. According to social capital theory, users can gain social capital on an individual and relationship level from such informational exchanges with their colleagues (Steinfield et al. 2008). Our interviewees state that being well-connected in the digital workplace can be one aspect of several important aspects for a promotion. Congruent with that, they also state that there are a number of colleagues who are particularly involved in communication and collaboration, for example, because they are experts in a particular field. Therefore, it might be possible that some of these users are hidden leaders or experts of some sort.

Managerial Implications

Our contributions can be used to help practitioners with addressing *six* of the practical challenges for collaborative work in the digital workplace, which Köffer (2015) extracted through a literature review. First and most generally, we show a way to *monitor general work behaviors (1)* through digital trace data with our study. While privacy issues might limit the usefulness of such an analysis in an organizational context, our approach does provide a way to investigate how communication and collaboration systems are being used on an organizational level. This might help organizations to assess the overall adoption rates and identify areas for improvement. It could also be interesting for platform owners, who can study which features – if defined as interaction types – are being used by which user groups. Second, Maruping and Magni (2015) report that with the diversity of work practices, no *one size fits all* strategy regarding the incorporation of collaboration technology can be pursued. With our typology of user roles, we provide guidance for practitioners to *segment employees (2),* not only regarding their collaboration behavior but also regarding their communication requirements (Cameron and Webster 2013). Third, through identifying different user types in our study, we also help organizations to better understand user needs based on which they can *provide support and training (3)* tailored to the individual needs of their employees. As mentioned in the Empirical Study subsection, for data privacy reasons, it would be challenging for organizations to recreate this analysis in order to identify individual employees. However, in our analysis of covariates of cluster membership, as well as our qualitative interviews, we described the user types and their characteristics in-depth. This might help organizations to target entire homogeneous groups of knowledge workers with their support or training efforts rather than individual users. Fourth, and connected to the previous point, through the identification of Passive Users, employees with a small number of ties can be encouraged to interact with others (Zhang and Venkatesh 2013), which in turn helps to *enable social interactions (4)*. Fifth, by getting a better idea of the communication and collaboration requirements of each hierarchical level, practitioners are also supported to more adequately *consider individual characteristics (5),* such as digital skills and experience, in their hiring or promotion decisions. For example, the 9% of full-time employees that reside in the High-activity All-rounder cluster and the Email Heavy-Users cluster might be candidates for a more communication-heavy job in management. Last, top management support is often cited as a critical success factor for the adoption of new software tools and for a positive knowledge-sharing culture (e.g., Wang and Noe 2010). We found that middle managers are particularly engaged in communication and collaboration as per their job requirements, which might make them better advocates to *demonstrate leadership* (6) on novel (social) collaboration platforms or ESN.

Limitations and Future Research

Our study has a number of limitations and leaves room for further research. While our data set is taken from an organization that is well-suited to study knowledge workers in the digital workplace, it only represents a small sample of knowledge workers. Additionally, we only capture white-collar knowledge workers with our study. Therefore our results cannot necessarily be generalized to other knowledge workers, such as healthcare practitioners or engineers. Also, while many of the user types found in this study overlap with those identified in previous studies in other settings, we cannot say with certainty that these user types are also inherent in the social structure of other organizations. Therefore, further research based on different data sets is necessary to validate the generalizability of our findings. Likewise, we follow an "eye of the beholder" clustering approach, which leans heavily on the interpretation of the identified clusters. While we provided extensive qualitative details to support our selected clustering solution, this remains an explorative approach that, again, needs to be validated in future research contributions. The maturity of the software usage within the organizations and personal IT skills could be considered to draw comparisons between organizations. A problem that is frequently mentioned in the context of SNA based on digital trace data is that, by definition, it only considers social interactions within the software environment. For example, it neglects undocumented face-to-face interactions and interactions through other software tools (Wang and Noe 2010). Howison et al. (2011) caution not to over-interpret the number of digital events between employees because the intensity and content of the interactions are unknown. Yet, researchers could define more distinct interaction patterns for future work to distinguish further between user types. For example, Gleave et al. (2009) present different ego-networks and hypothesize that their shapes can give hints about the roles of actors. Additionally, for privacy reasons, our analysis neglects the content of the interactions and the actual information flows transmitted through them. *Hashing* and *speech acts* have been used in the past to allow for an automatic analysis while maintaining the anonymity of the data (Carvalho and Cohen 2005; van Alstyne and Zhang 2003) and could be applied to this context as well. Another interesting question for further research is whether the employees keep or change their user roles over time. And if they change, what external factors cause those role changes. Researchers in the context of Wikipedia have found turbulent stability of emergent roles, which describes the phenomenon that individual user roles may change, but the overall composition remains the same (Arazy et al. 2016).

Conclusion

In this study, we addressed the need to gain a better understanding of the heterogeneous behaviors of knowledge workers within their digital workplace in an organization. The importance of this question is rooted in the understanding that one size fits all solutions regarding the incorporation of such software into the diverse work practices are not adequate. Therefore, and to improve our knowledge of how these work practices differ, we set out to identify emergent user roles of a communication and collaboration environment. This endeavor is rooted in the knowledge-based theory of the firm and social capital theory, as well as in a fragmented body of research on the digital workplace and user roles in digital communication and collaboration environments. As a result of cluster analysis, we found eight distinct user roles. In contrast to other studies in different contexts, we found that the presence of organizational roles can help explain many behavioral differences through factors such as the organizational hierarchy and the individual job requirements of the users. Those findings are routed in a quantitative analysis of influencing factors and qualitative user interviews. We observe that, congruent with the organizational knowledge creation theory, top managers are heavily involved in communication, while middle managers bridge the gap between top managers and employees by turning visions into tangible content. For user types that distribute information and provide content, we observed usage patterns that can be explained through an in-role understanding of knowledge sharing. Similarly, for employees who are heavily involved in tasks that require teamwork, a tendency towards co-creation of content with colleagues was observed. Lastly, and congruent with the positive effects of social connections on social capital, we argue that outliers can potentially be hidden leaders and candidates for promotions. With our approach, we contribute to the scientific progress in the field and support practical implications of communication and collaboration in the digital workplace. Future research should refine our interaction types and validate our findings with different data sets, particularly through but not limited to longitudinal designs.

3.2. How DTM Users React to Real-Time Feedback

Another perspective relevant to individuals' DTM use behavior is their response to certain design elements of information systems. Systems aiming to facilitate a behavior change typically implement interventional techniques. The following research activity explores this at the example of one of the greatest challenges of our time – the reduction of greenhouse gas (GHG) emissions. The building sector accounts for 30 percent of the total energy consumption worldwide (International Energy Agency 2018), and increasing the energy efficiency of buildings is a promising lever to achieve a reduction of GHG emissions. A common measure to raise the energy efficiency of buildings is the improvement of the building's insulation (Fowlie et al. 2018; Hardy et al. 2018). However, high insulation is also linked to a decrease in buildings' indoor environmental quality (IEQ) (Wadden and Scheff 1983). Poor IEQ can cause detrimental effects on human health, well-being, and productivity (Fisk and Rosenfeld 1997; Steinemann et al. 2017) and is associated with a broad range of negative long-term effects such as severe respiratory diseases or decreased decision-making performance (Fisk and Rosenfeld 1997; Wei et al. 2015).

A widespread countermeasure against poor IEQ in well-insulated buildings is the implementation of heating, ventilation, and air conditioning (HVAC) technology (Homod et al. 2014; Wyon 2004), but the energy consumption is a grave drawback of HVAC (Chenari et al. 2016; Homod et al. 2014). Alternatively, natural ventilation, for example, by means of manual airing, is promoted as an energy-efficient solution to maintain the positive effect on air quality and health (Chenari et al. 2016; Schibuola et al. 2016). However, occupants often struggle to strike the right balance of ventilation, for example, because they do not sense the gradual deterioration of environmental quality. Therefore, Schibuola et al. (2016) recently called for the use of real-time feedback on the IEQ to trigger the occupants' manual airing but do not yet provide empirical evidence. Feedback is one means of (digital) nudging, which aims to influence human behavior unobtrusively (Weinmann et al. 2016). However, nudges need to be planned carefully as they must catch the user's attention to work properly (Hummel et al. 2018). Against this background, we aim to contribute to a better understanding of the applicability of digital devices to nudge incidental activities – such as opening the windows – in an environment that requires a strong focus on the primary tasks – such as work. In this context, it is unclear if a nudge can catch the occupants' attention and motivate them to suspend work in order to ventilate. Therefore, we elaborate on the following research question: *Can real-time feedback on indoor environmental quality effectively nudge office occupants in a computer-dominated work environment towards natural ventilation in order to improve the indoor environmental quality?*

We employ a field experiment with a total of 32 occupants in 15 shared offices of a German research institute to investigate the effectiveness of nudging natural ventilation. This is done by means of a prototypical, sensor-based display screen providing visual and quantitative feedback on the office's current IEQ. Our digital nudge aims to make the occupants aware of poor IEQ and, thereby, implicitly influence behavior but does not directly hint at opening the windows. In our evaluation, we found differences in IEQ when comparing the treatment group before the nudge and with the nudge as well as when comparing the treatment group with a control group, which did not get any feedback. The results indicate that the nudge induces a behavior change towards opening the windows regularly when the IEQ drops. While this effect is strong in the first days of the experiment, it decreases over time and converges to an IEQ higher than the baseline without a nudge. A survey with 17 of the 32 participants further substantiates the effectiveness of the nudge based on the participants' self-perception.

This section is structured as follows. The first subsection aims to establish a common understanding of the assessment of indoor environmental quality and the concept of (digital) nudging. The research design and methodology are presented in the second subsection. The third subsection describes the study's results. The theoretical and practical implications of our research are discussed in the fourth subsection. Finally, the work concludes with a critical view of the study and an outlook on future research.

Related Work

Indoor Environmental Quality

A multitude of studies show that the quality of the air we breathe can have a significant impact on our health (Jones 1999). The same holds true for other environmental factors such as thermal comfort and noise (Almeida et al. 2015). Other studies find that humans spend a large majority of their time indoors: A large-scale study funded by the US government found that the percentage of time Americans spend inside buildings is as high as 87 percent (Klepeis et al. 2001). These two streams combined are the motivation for research in the context of indoor environmental quality, which aims to establish an indoor environment worth living in. This topic gained importance with improved insulation in energy-efficient buildings accounting for reduced air exchange and, thus, limiting IEQ (Wadden and Scheff 1983).

Poor IEQ is linked with severe health issues and impaired well-being (Steinemann et al. 2017; Wolkoff 2018). Besides negative short-term effects like the *Sick Building Syndrome*, literature listed a broad range of detrimental long-term consequences of bad indoor environments, including respiratory diseases and decreased performance in decision-making (Fisk and Rosenfeld 1997; Spengler 2012; Wei et al. 2015). IEQ has also been shown to have a major impact on the occupants' productivity in office environments (Fisk and Rosenfeld 1997; Wyon 2004). While these effects primarily impact the individual that is exposed to poor IEQ, healthcare costs and loss of working hours may also adversely affect the economy and society.

IEQ includes various aspects that influence life inside buildings. However, the particular aspects differ depending on the use case. In its most narrow form, it is similar to the concept of indoor air quality, commonly referred to as IAQ, but can also include hygiene, noise, vibration, among other factors (Mujeebu 2019). In our study, we apply the Indoor Environmental Index (IEI), an index proposed by Moschandreas and Sofuoglu (2004). It describes IEQ primarily based on air quality and thermal comfort and consists of two sub-indices, the Indoor Air Pollution Index (IAPI) and the Indoor Air Discomfort Index (IDI). IDI evaluates the thermal comfort (or discomfort) experienced due to the temperature and relative humidity in the room. IAPI additionally assesses the amounts of organic gases (formaldehyde and total volatile organic compounds (TVOC)), inorganic gases (carbon monoxide and carbon dioxide (CO_2)), total particulate matter (PM10 and PM2.5), and biological particulate matter (bacteria and fungi) in the air. Both values are combined to an index ranging from 0 to 10, where 0 denotes very good environmental quality, and 10 represents very poor environmental quality.

Several solutions have been proposed in the literature to improve IEQ. In highly insulated buildings, HVAC technology is often applied to ensure regular air circulation. However, HVACs have a vastly negative impact on the building's energy consumption (Chenari et al. 2016; Homod et al. 2014). Several studies, therefore, investigated the potential of natural ventilation and window airing and found that short-term window airing can significantly improve IEQ (Heiselberg and Perino 2010). Therefore, we aim to investigate the potential of digital nudges to help people acquire a desirable ventilation behavior.

(Digital) Nudging

People often have several options for action in different situations in their lives. To make a decision, the processing of information is required. Thereby, heuristics are often applied to facilitate and accelerate the decision-making process by reducing the amount of processed information (Chaiken and Trope 1999). However, heuristics can lead to biases, i.e., systematic errors, like misjudging probabilities (Tversky and Kahneman 1974). This builds the theoretical foundation for nudging, which is a concept based on insights from behavioral economics and has been proposed by Thaler and Sunstein (2009). It aims to change environments and situations in such a way as to increase the probability of certain behaviors. Thus, these changes could ultimately lead to a different decision.

Nudging can be applied in various settings and involve different techniques. Nudges, which are single instantiations of nudging, are designed in such a way that neither financial incentives are set, nor something is prohibited or directly recommended to influence people's behavior. Table 10 provides an exemplary list of nudges that are widely used in literature. One type of nudge is the incentive. It is described by Hansen and Jespersen (2013) as making the consequences of a choice visible because visible information can be processed more easily. The salience nudge uses this by taking advantage of a cognitive bias that predisposes individuals to focus on items that are more prominent or emotionally striking (Bordalo et al. 2012). A typical nudge used in many application domains is setting defaults. It uses individuals' tendency to stick to the status quo and takes advantage of their resistance to change (Coch and French 1948). Another technique to nudge an individual is providing feedback (Weinmann et al. 2016) with the goal to evoke a certain behavior or change of behavior. Social norms, on the other hand, are rules of society that differ from culture to culture and make up what is seen as normal, acceptable, and respectful behavior (Bénabou and Tirole 2006). Using this can influence individuals showing the same behavior as the social group (Mirsch et al. 2017). Croson and Shang (2008) showed that people tend to adapt the amount they donate when they are presented with social norms. When they are told that most people donate less than them, they also donate less, and vice versa. While this list of nudges is not exhaustive, it helps to demonstrate how nudging can influence an individual's subconscious and therefore, decision making.

Transferring the concept of nudging into the context of information systems enables further possibilities to nudge individuals to a certain behavior. Weinmann et al. (2016) describe digital nudging as guiding individuals' behavior by means of digital user interfaces and several studies have yet examined the effectiveness of digital nudging.

Enabled by the ubiquity of sensor technology, feedback has become a common way of nudging, for example, in the context of energy efficiency (Heger et al. 2020; Jensen et al. 2016; Tiefenbeck et al. 2019; Wargocki and Da Silva 2015). Tiefenbeck et al. (2019) evaluate the effect of real-time feedback on energy use during showering. Wargocki and Da Silva (2015) demonstrate the effectiveness of CO_2 feedback in school environments to improve classroom air quality. Jensen et al. (2016) investigate the social effects of CO_2 feedback devices in residential buildings. While these studies address related questions, to the best of our knowledge, research yet fails to evaluate the effectiveness of real-time IEQ feedback to change ventilation behavior in a work environment, in which people focus on their primary tasks. Our work approaches this question and aims to give first indication of the effectiveness of nudging in this context.

Nudge	Description	Study showing effectiveness
Incentive	Showing consequences of the decisions made (Hansen and Jespersen 2013) – not to be confused with financial incentives, which are not considered as a nudge. An example would be the display of costs for an ongoing call. It does not change the charging model but might lead to shorter calls.	Noar et al. 2016
Salience	Designing important information in such a way that they are more visible (Mann and Ward 2007).	Pahuja and Tan 2017
Default Setting	Using default settings to remain with the status quo (Mirsch et al. 2017). An example would be the current discussion about changing the default of organ donors from opt-in to opt-out.	Goldstein et al. 2008
Giving feedback	Providing users with feedback when they are doing well or making mistakes (Weinmann et al. 2016). An example would be an electronic road sign that reacts to the vehicle's speed with a smiling or sad face.	Tiefenbeck et al. 2013; Tiefenbeck et al. 2019
Social Norms	Providing information about rules, standards and, appropriate behavior within a group of people (Dolan et al. 2012).	Bond et al. 2012

Table 10: Exemplary Nudges and Studies Showing Their Effectiveness

Research Design

This work aims at better understanding the effect of real-time IEQ feedback, as a means of digital nudging, on human ventilation behavior in a work environment. We collect empirical evidence, analyze ventilation behavior under the influence of nudging, and evaluate user acceptance of the nudge in a field experiment. The following subsections describe the experimental setup of the field experiment and the collected measures.

The field experiment

In the field experiment, we collect empirical evidence for the feasibility of digital nudging in a German university-based research institute. Since most work is performed via the computer, activities are predominantly sedentary. The experiment includes 15 offices equal in size and layout and reaches 32 constant office occupants, of which 23 are male and nine female. All participants are in the age range of 25 to 40 years. We refrained from including additional offices, although it would have increased the sample size since their layout differed substantially from the selected offices and would introduce additional confounding factors affecting the statistical analysis. Initial office selection further catered for planned absence to ensure continuous office presence throughout the field experiment. Thus, the chosen sample size allows for maximum comparability among offices. Before starting the experiment, offices were randomly assigned to either the control group (seven offices) or the treatment group (eight).

The study took place over four weeks in the cold season in February and March 2019. During that time, both groups were equipped with a data logger measuring the office's IEQ. To build a baseline for comparison, there is no nudge for neither the treatment nor the control group in the first two weeks of the experiment, but the sensors already collect IEQ data. In the second phase, the nudge phase, offices in the treatment group are additionally equipped with a display that provides real-time IEQ feedback, while the experimental setting remains unchanged for the control group. Both the data logger and the display were only installed with the occupants' prior consent. Participants were unaware of the exact goal of our research but were informed that the study aims to assess the building's environmental quality. They were further unaware whether their office was in the control or the treatment group until the beginning of the nudge phase. Figure 8 illustrates the experimental setup.

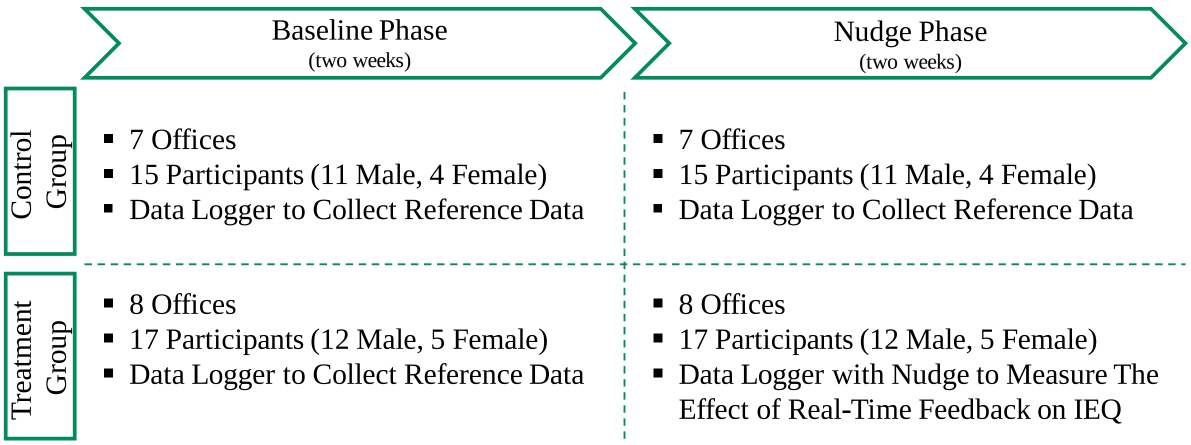


Figure 8: Experimental Setup

The setup of the field experiment enables us to compare the ventilation behavior between the treatment and the control group, but also within the treatment group before and with the nudge. Based on the experiment design, we claim that the nudge is the most plausible explanation for differences in behavior between the groups and phases.

Measures

In order to analyze the participants' ventilation behavior, various measures are collected throughout the experiment. This includes environment data from the data loggers, based on which an Indoor Environment Index (IEI) is derived for the nudge. Finally, we conducted a survey to capture participants' self-perception and user acceptance. The following subsections describe the data logger, the nudge, and the survey in more detail.

The data logger

At the beginning of the field experiment, we installed data loggers measuring IEQ parameters in all participating offices. The data logger collects data on the office's temperature (in ºC), relative humidity (in %) as well as the carbon dioxide (CO_2, in ppm, that is, parts per million) and total volatile organic compounds (TVOC, in ppb, that is, parts per billion) concentrations. The data loggers are prototypically built with Arduino microcontrollers, Raspberry Pi single-board computers, and sensor modules. Figure 9 displays the technical infrastructure.

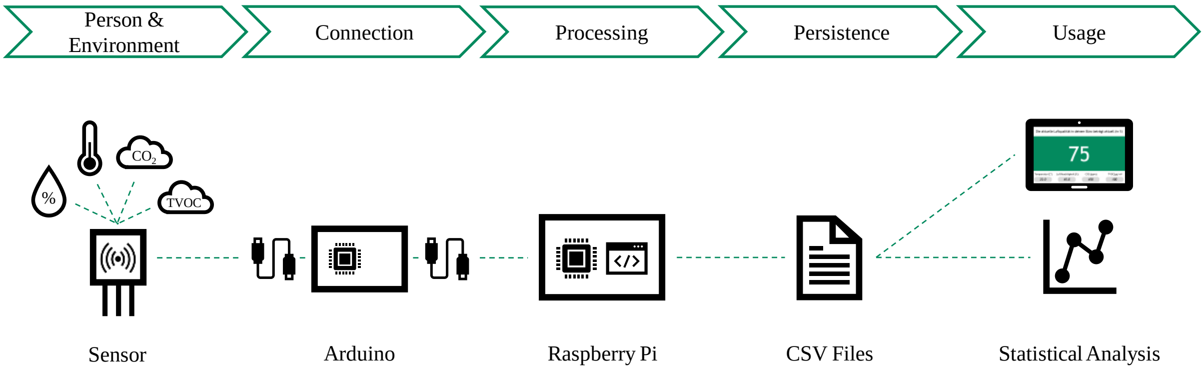


Figure 9: Data Logger Prototype Aligned With the JDCF Data Flow by Beckmann et al. (2017)

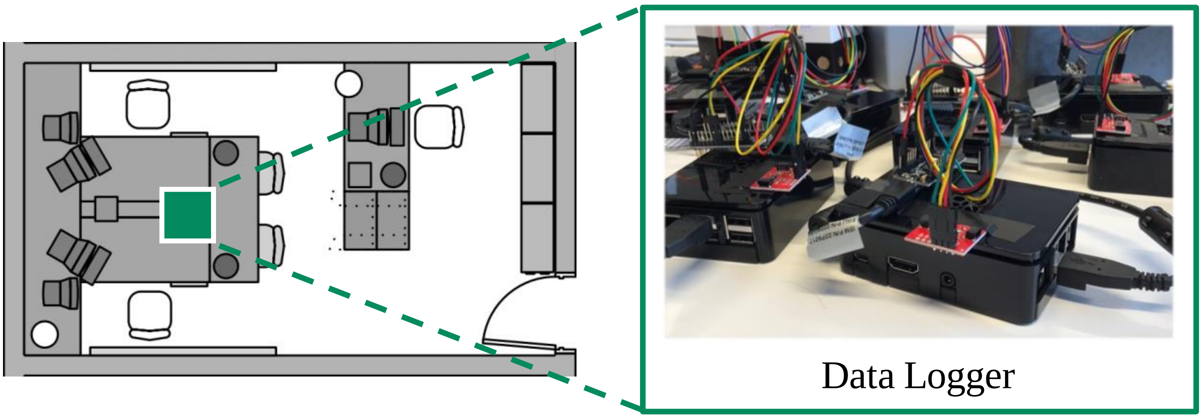


Figure 10: Typical Structure of an Office and Placement of the Data Logger

Technically, it uses the Java Data Collecting Framework (JDCF) from Beckmann et al. (2017) to collect and process data. Following their suggestion, we describe the data flow along the dimensions *Person & Environment*, *Connection*, *Processing*, *Usage*, and *Persistence*. For the *Person & Environment* step, a combined sensor for humidity, temperature, CO_2, and TVOC collects environmental parameters of the office. To establish the *Connection*, an Arduino probes the sensor in an interval of five seconds and reads sensor data via an I²C bus using a C program. Raw data then is passed via USB to a Raspberry Pi, which utilizes an implementation of the JDCF to realize the *Processing* part. Finally, the data logger uses comma-separated value files as the *Persistence* form to prepare data for further *Usage* within a statistical analysis.

We place the loggers on top of the desk approximately in the middle of each office and at least 50 centimeters away from all large technical devices (Figure 10) in order to obtain comparable and reliable sensor data. Staff is instructed not to move the data loggers. To prevent problems resulting from the use of low-cost sensor technology, all sensors are calibrated against a high-quality sensor before the start of the experiment.

The nudge

In order to nudge the participants towards natural ventilation in case of poor IEQ, we base on the concept of visualizing feedback. Therefore, after two weeks of data collection without feedback, we attach the Raspberry Pi of the treatment group to the backside of a seven-inch display and use a 3D-printed bracket to ensure an upright placement of the display. Based on sensor data from the data logger, this display allows us to provide feedback on the current IEQ of the office. To do so, we aim to design and develop an interface that catches the user's attention and nudges them towards opening the windows without explicitly requesting it. Therefore, we divide the screen into the main part that shows an aggregated value for the IEQ and a bottom part that additionally displays the raw sensor values of the temperature, relative humidity, CO_2, and TVOC sensors. The screen refreshes in intervals of five seconds.

To make IEQ more tangible in the main part of the display, we use an adapted version of the Indoor Environmental Index (IEI) proposed by Moschandreas and Sofuoglu (2004). This adapted IEI (aIEI) differs from the original form in two ways: First, we omit several pollutants such as bacteria or fungi, which are included in the original form, but quite expensive to measure. Second, for presentation purposes, we transform the original scale (0 to 10, where 0 denotes the best environmental quality) to the more intuitive 100-to-0 scale, where 100 is the best value. The calculation of the aIEI builds on data from the last fifteen seconds to avoid erratic changes and increase robustness.

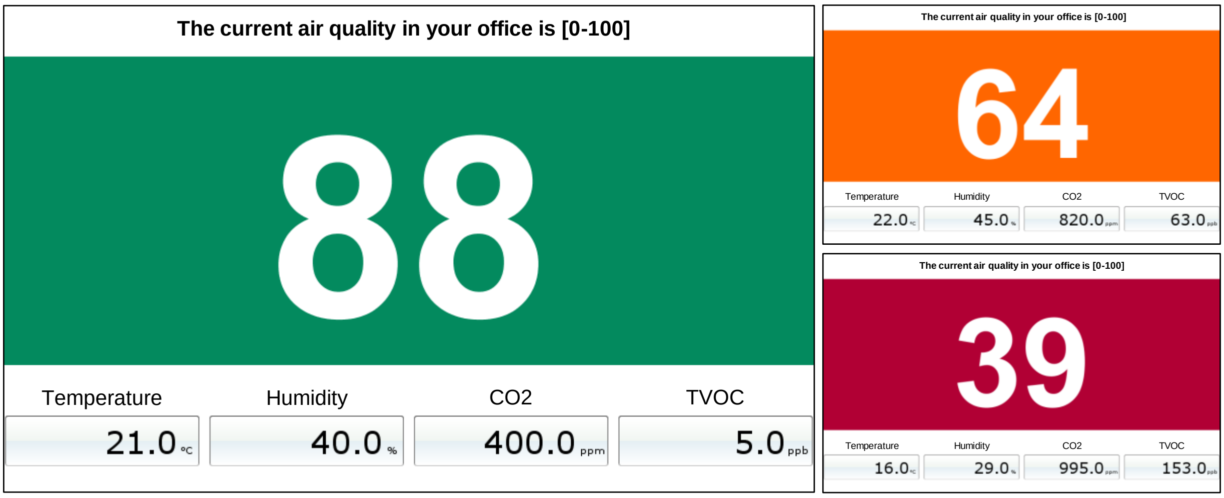


Figure 11: User Interface of the Display

The nudge uses different background colors (Figure 11) for the display's main part to emphasize the numerical aIEI value. Following related work on emotional feedback (Astor et al. 2013; Jensen et al. 2016), colors range from green to red. The background is green at values 65 or above, orange with an average environmental quality below 65 but at or above 40, and red when the aIEI drops below 40. While these limits are based on the data collected within the baseline phase, they align with descriptive IEI statistics (Moschandreas and Sofuoglu 2004).

The survey

In order to further support our findings, we conduct a survey after the experiment. The survey comprises overall 20 items with a five-level Likert scale as well as free text fields. Besides collecting data on office presence and occupancy, items are inspired by the technology acceptance model (Venkatesh and Davis 2000). Therefore, items are grouped in personal preferences and attitude, perceived usefulness of the provided feedback, and the perceived ease of use of the provided display, including the frequency of use. In accordance with our research question, we further asked if the participants perceived the displayed feedback as distracting and if the continuous use of the feedback is imaginable. Items on personal preferences and attitude were, for example, "Good air quality is important for me" and "I perceive the indoor air quality in my office as good." Items on the perceived usefulness of the provided feedback were, for example, "My ventilation behavior has changed due to the provided feedback," "I perceive the feedback as distracting," and "The air quality has improved due to the feedback." Finally, we include free text fields for participants to provide both positive and negative feedback.

Results

The experiment yields a dataset that comprises the levels of CO_2, TVOC, relative humidity, and temperature in 5-second intervals for 15 offices over four weeks in February and March 2019. This subsection outlines the findings obtained from analyzing this dataset. Our analysis is inspired by similar research on digital nudging (Tiefenbeck et al. 2013; Tiefenbeck et al. 2019).

We performed several steps of data preprocessing to prepare raw data for data analysis. First, to account for small time offsets and maintain comparability among different offices, we split data into 15-second intervals and averaged the values within that interval. Second, we removed the weekends to exclude days with a very low presence of occupants. Third, we calculate the aIEI for each time interval and office based on this dataset. The resulting dataset consists of $N = 1{,}728{,}000$ IEQ observations with a mean aIEI of 47.91, a median of 48.24 and a standard deviation of 15.42. Thereafter, we separated the dataset into treatment and control groups and pooled it according to the two experiment phases (baseline and nudge). We then derive the daily mean aIEI per office for each group and phase. Table 11 summarizes the resulting descriptive statistics.

Group	Phase	Min	5th %ile	Median	Mean	95th %ile	Max
Control	Baseline	31.60	35.88	50.93	50.77	63.85	72.40
	Nudge	26.94	30.02	50.79	50.10	67.05	73.92
Treatment	Baseline	21.33	27.68	46.34	45.71	57.91	63.06
	Nudge	22.60	29.12	48.44	49.83	72.05	81.41

Table 11: Descriptive Statistics of Control and Treatment Groups' aIEI

The results indicate that the control group's ventilation behavior did not change throughout the experiment since both median and mean during the nudge phase are on a similar level during the baseline phase. In contrast, a clear upward shift of all analyzed values can be observed for the treatment group, although their aIEI on average is below the level of the control group. Comparing the mean aIEI from the control group to the treatment group's IEQ mean during the baseline phase, the control group had an 11.07% higher IEQ compared to the treatment group. However, during the nudge phase, the control group's IEQ was only 0.54% better. The initial discrepancy in the baseline phase may be a result of the small sample size and individual differences in both groups.

The highest gain can be observed in the 95th percentile and maximum values with an increase of 24.42% (72.05, compared to 57.91 without feedback) and 29.10% (81.41, compared to 63.06 without feedback). This indicates that nudging successfully raised awareness for IEQ.

Consequently, more offices reached a high aIEI on a daily basis, which is a promising sign for our experiment. However, the marginal change in the lower range of aIEI values also reveals that some offices did not change their behavior due to the nudge. The boxplots in Figure 12 illustrate the differences between the groups in each phase based on daily averages.

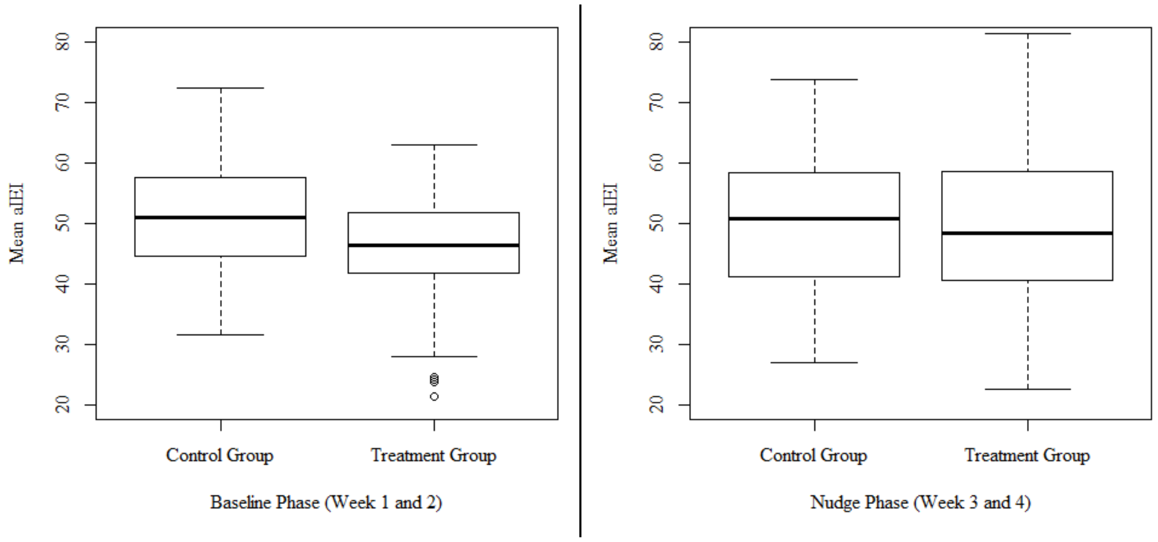


Figure 12: Mean aIEI of Baseline and Nudge Phase

We aim to analyze the significance of the shift in the aIEI mean between the experiment phases. To do so, a paired two-sample *t*-test is a common approach, for example, in Tiefenbeck et al. (2013). For a *t*-test to be applicable, the mean of the two samples should follow a normal distribution. Hence, we test each dataset for normality using the Shapiro-Wilk-Test. Table 12 summarizes the results. Since $p > .05$ for all data sets, the normality assumption holds.

Group	Control Group		Treatment Group	
Study Phase	Baseline	Nudge	Baseline	Nudge
***p*-value**	.9371	.1885	.2236	.5299

Table 12: Shapiro-Wilk-Test for Normality – Overview of the Derived p-Values

To account for possible autocorrelation within the time series, we apply the Ljung-Box test, which again yields $p > .05$ for all datasets. Thus, we have no autocorrelation and can perform a paired sample *t*-test to test the significance of differences in the mean between the two experiment phases. The results are summarized in Table 13.

Perspective	Control Group	Treatment Group	Baseline Phase	Nudge Phase
Comparison	Baseline vs Nudge	Baseline vs Nudge	Treatment vs Control	Treatment vs Control
$\mathbf{N_{treatment}}$	70	80	80	80
$\mathbf{N_{control}}$	70	80	70	70
***p*-value**	.684	.014*	< .001***	.897
***t*-statistics**	0.41	-2.53	3.56	-0.13
df	69	79	146.58	147.76

Table 13: Paired Sample t-Test of Pooled IEQ Data for Baseline and Nudge Phase

For the control group, we expect to see no change in ventilation behavior and aIEI across both phases, as no feedback on the IEQ was provided. We can confirm this expectation statistically since the change in the control group's aIEI across the experiment duration is not significant with $p_{\text{control}} = .684$, $t(69) = 0.41$. In contrast, the treatment group significantly improved their aIEI with $p_{\text{treatment}} = .014^{*}$, $t(79) = -2.53$ in the nudge phase when compared to the baseline phase. Thus, we can assume that the nudge, on average, did have a measurable impact on the targeted ventilation behavior.

The survey results of 17 of the 32 occupants substantiate our statistical findings regarding the nudge's effectiveness. Eleven participants from the treatment group and six from the control group took part in the survey. According to the survey, only six of all 17 survey participants (35.29%) consider the indoor air quality in their office to be good, although 16 participants (94.12%, n=17) agree that good indoor air quality is generally important to them. Furthermore, ten of the 11 survey participants of the treatment group (90.91%) confirmed that they used the display to evaluate their IEQ on a frequent level. The same number of participants in the treatment group states to have changed their natural ventilation behavior due to the provided feedback, which is in line with our statistical findings. Furthermore, only two participants in the treatment group perceived the feedback as distracting, whereas seven participants (63.64%, n=11) stated that they did not feel distracted. Overall, three-fourths (75.00%, n=16) of all survey participants would like to (continue to) use such a device to monitor their IEQ.

However, a closer look at the treatment group in the nudge phase qualifies the findings of the nudge's effectiveness in part. For the purpose of this analysis, we visualize the average aIEI during the nudge phase for the treatment group (Figure 13; further visualizations are presented in Appendix A.1) in 15-seconds intervals. In this course, we identify a downward trend in the treatment group's mean aIEI over the two weeks of nudging. This trend indicates that the nudge has a significant effect at the beginning of the experiment, but its effectiveness reduces over time. At the end of week 4, it finally converges to a level, which is higher than the treatment group’s mean aIEI in the baseline phase. This is in line with other nudging experiments and is commonly explained with a habituation effect towards the nudge (Tiefenbeck et al. 2013; Tiefenbeck et al. 2019).

To overcome habituation effects, we recommend to regularly adapt the nudge to preserve its positive effects on the ventilation behavior. This can, for example, be accomplished by personalizing the nudging limits and set individual goals regarding the ventilation behavior.

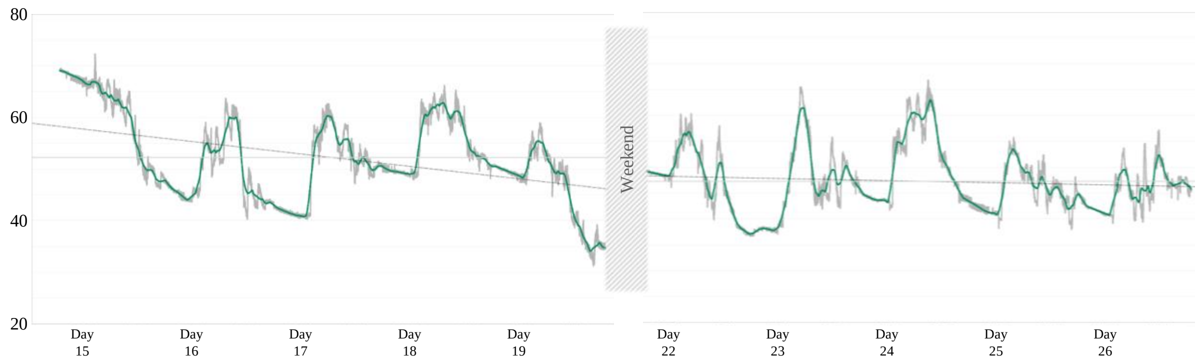


Figure 13: Average aIEI Development in the Nudge Phase – Treatment Group

Another evidence for the high relevance of inter-personal differences emerges when looking at the individual IEQ charts of single offices. As assumed from the descriptive statistics, some offices did not change their behavior. This might explain the marginal change in the lower IEQ segment. While we do not exactly know why the nudge did not work for them, we assume that low interest in IEQ, resistance to change their habits, work stress not leaving time for incidental activities, or specific personality traits are possible influencing factors. One participant confirmed in the free text field of the survey that work stress has an influence on their perception of IEQ and stated to have covered the display because the changing IEQ values distracted them from their work.

Discussion

The study presented in this work has several theoretical and practical implications. Our research contributes to theory by laying important groundwork for a better understanding of how to design nudges. Specifically, we find that people might get used to the nudge and argue that the design of interventions should account for this habituation effect by incorporating a longitudinal evaluation of the nudge’s effectiveness.

From a practical point of view, it presents empirical evidence that real-time feedback based on low-cost technology is an effective means to positively influence ventilation behavior and, thus, help improve the IEQ in a working environment, where ventilation is a secondary task. This bases on the finding that the treatment group's IEQ on average significantly improved in the nudge phase compared to the baseline phase in a paired sample *t*-test, while there is no significant difference for the control group. A survey further substantiates this claim and indicates increased awareness among the test office occupants for air quality and its related health issues as a result of the nudge. It also shows that some participants are enthusiastic about establishing real-time IEQ feedback over the long term to foster an air-quality- and health-conscious working environment.

Conclusion

In this study, we conducted a field experiment to test if real-time IEQ feedback can effectively nudge occupants towards opening the windows in an office environment, where most work is performed at the computer and ventilation is a secondary task. We investigated sensor data from 15 shared offices with 32 participants collected over four weeks. During the last two weeks, the nudge phase, occupants of offices in the treatment group received real-time feedback on the office's IEQ via a display in the office. The control group did not receive any feedback during the time of the experiment.

Although we conducted this field experiment with the necessary care, limitations restrict the informative value of our results. First of all, we find that the nudge's effectiveness reduces over time. While the average IEQ in the treatment group strongly increases in the first days of the nudge phase, the same cannot be found at later days. Possibly as a result of habituation to the nudge, the IEQ level in the treatment group finally converges to a level, which is higher than in the first two weeks of the experiment. Second, although the treatment group's IEQ on average improves with the nudge, we see high variations in the offices' individual IEQ profiles. In some offices of the treatment group, we can observe no or only a little difference between the phases with and without a nudge. This might be explained by people's different personality traits or attitudes towards IEQ and their own health, but also as a consequence of work stress that does not leave time for incidental activities such as opening the windows. Third, we aimed to control as many external factors as possible that may have an impact on the result while not interfering with the participants' daily work and habits. Nevertheless, factors exist that were not controlled during our study due to restrictions regarding the interference with the daily work routine (e.g., requiring a certain behavior) or sample size (e.g., the position of the office inside the building).

Future research should address these issues by gathering more data in general as well as in multiple cases differing in their geographic location to verify external validity. Further studies should also build on our work by evaluating the effectiveness and longevity of IEQ nudges. This could be achieved by comparing different designs of nudges, for example, by adding elements of gamification and competition to increase motivation. Finally, a closer look into inter-personal differences of the nudge's effectiveness is yet missing and might build the foundation for the design and development of personalized nudges.

In general, the findings of our study lay important groundwork to better understand how to guide people towards changing their ventilation behavior. In times in which an increasing number of buildings are highly insulated, maintaining a good IEQ is important to preserve the occupants' health. According to research, manual airing still is the best method to achieve a good indoor climate while saving our planet.

4. Analyzing Individuals' Responses to Consequences of Their DTM Use

Influenced by individuals' behavior which has been investigated in the previous chapter, digitalization may have various consequences on individuals (Matt et al. 2019). While it is generally appreciated for making people's lives easier, increasing work efficiency and productivity, and fostering a societal transformation that leads us into a bright future, its dark sides must not be overlooked (Gimpel and Schmied 2019; Tarafdar et al. 2015b; Tarafdar et al. 2015a; Turel 2019). Phenomena such as technostress (Ayyagari et al. 2011; Ragu-Nathan et al. 2008; Tarafdar et al. 2011), information overload (Karr-Wisniewski and Lu 2010), IT addiction (Turel et al. 2011b), security and privacy concerns (D'Arcy et al. 2014), and cyber-bullying (Weinstein and Selman 2016a) have the potential to significantly impair individuals' well-being and health and cause economic damage. A research stream that has gained particular attention in the IS literature over the past years strives to understand stress directly or indirectly resulting from ICT use, commonly referred to as digital stress or technostress[4,5] (Ayyagari et al. 2011; Brod 1984; Ragu-Nathan et al. 2008; Weil and Rosen 1997).

A population at high risk of suffering from the cognitive, psychological, and physiological outcomes of technostress are adolescents (Compas et al. 2001; George and Odgers 2015). They encounter ICT such as smartphones or social media daily (George and Odgers 2015), often spend more time of the day with ICT than they are at school or sleep (Rideout and Robb 2019), and have a significant amount of their social interactions via ICT (Turner 2015). Adolescents' interaction with ICT fundamentally differs from that of adults, with a stronger emphasis on ICT use for entertainment and communication purposes than in older age groups (Pfeil et al. 2009). This usage pattern might increase exposure to stressful encounters (George and Odgers 2015) and makes the dangers an inescapable part of their lives. Simultaneously, adolescents are still amid their psychosocial development (Erikson 1959) and lack vital skills to deal with the rising demands of the digital world. Their struggle with developing a self-image (Simmons et al. 1973) and their experience of role confusion (Tanti et al. 2011) make them prone to peer pressure and addiction (Chambers et al. 2003), characteristics linked to ICT use (Turel et al. 2011b;

[4] Although stress can also act as a challenge (so-called eustress) (Tarafdar et al. (2019), the predominant focus of stress research in both psychology and IS literature is on the harmful effects of stress (distress). In this paper, we focus on techno-distress.
[5] Chapter 4 largely conforms with Schmidt et al. (2021).

Weinstein and Selman 2016a). Both aspects increase ICT-related demands on adolescents, potentially making them more vulnerable to technostress (George and Odgers 2015).

Despite their vulnerability, little is known about adolescents' ways of coping with technostress to prevent adverse outcomes. To the best of our knowledge, no study has yet created adequate knowledge on what coping responses adolescents activate to mitigate technostress and what individual and situational conditions influence their coping behavior. However, this perspective is highly relevant for two reasons. First, it helps advance theory on technostress coping at the example of a group of people presumed to be among those with the highest frequency of private ICT use and simultaneously is at high risk of suffering from its adverse outcomes. Second, it can produce practical knowledge that enables parents, teachers, and other adults to better protect the young from adverse outcomes of technostress, for example, by strengthening their coping competencies. Our research follows recent calls to shed light on the dark sides of digitalization at the individual level (Turel et al. 2019) and to examine coping in the context of technostress (Tarafdar et al. 2019; Weinert 2018). It contributes to technostress theory by extending the understanding of technostress coping with an overview of coping responses that adolescents activate to mitigate technostress and by providing empirical evidence for differences in the activation of coping responses across adolescents and technostress creators. We investigate two research questions:

RQ1: What coping responses do adolescents activate as a reaction to technostress creators?

RQ2: What factors underlie adolescents' activation of coping responses?

We apply a mixed-methods approach (Venkatesh et al. 2013; Venkatesh et al. 2016), combining a qualitative and a quantitative study. The results of the qualitative study lay the foundation for subsequent quantitative analysis. Study 1 employs qualitative workshops with 75 adolescents in three German school classes to identify technostress coping responses relevant to adolescents. It yields a list of 30 coping responses grouped into five categories. Study 2 builds on these results and analyzes data from a survey on technostress perception and the activation of coping responses with 230 adolescents aged 10 to 17.

Our results suggest that adolescents experience various technostress creators (highest: *Disclosure* of private information, lowest: *Complexity* of ICT) and can draw from a broad portfolio of coping responses. Exploratory factor analysis reveals five factors underlying adolescents' activation of coping responses. It unveils that adolescents' coping behavior differs depending on individual characteristics such as age, gender, and the number of owned devices, as well as on situational characteristics such as specific technostress creators. Although there is no 'one size fits all' approach to technostress coping, our findings suggest that supporting adolescents in developing the skills and behaviors to leverage a broader portfolio of coping responses might help them meet the demands of their digital life.

Theoretical Foundations

Early definitions describe technostress as "a modern disease of adaptation caused by an inability to cope with new computer technologies in a healthy manner" (Brod 1984, p. 16) or as "any negative impact on attitudes, thoughts, behaviors or psychology caused directly or indirectly by technologies" (Weil and Rosen 1997, p. 5). These definitions reflect that the use of ICT can be demanding and stressful for individuals. Since then, significant technological advances have been made. The use of ICT is no longer limited to a small number of people but ubiquitous and part of our everyday work and private life. As a result, technostress research has produced significant contributions in various disciplines to understand how ICT can create stress in individuals and what adverse outcomes can arise from technostress.

While early technostress publications almost exclusively focused on the stress created by ICT used due to an organizational imperative, more and more studies recently examined the stressing effects of voluntary ICT use. These studies indicated that technostress also arises from the private use of smartphones (Vahedi and Saiphoo 2018) or social networks (Maier et al. 2012, 2015a; Maier et al. 2015b; Salo et al. 2019) and might produce similar individual-level outcomes as organizational technostress (Maier et al. 2015b; Salo et al. 2019).

Thereby, the occurrence of technostress follows a similar logic: most of the technostress creators from section 2.3 have been confirmed for both the organizational and the private ICT use (*overload*, *invasion*, *complexity*, *uncertainty*, *unreliability*, *disclosure*), whereas some have been examined only for the work (*insecurity*) or the private context (*social pressure*). The large overlap between work and private technostress creators is likely because peer expectations substitute the role of organizational requirements and create a demand (Maier et al. 2012). Some of these technostress creators have already been researched in adolescent populations. Social overload and information overload, for example, did not prove to be considerable technostress creators for adolescents, although more than a third of the surveyed adolescents perceived that they spend too much time on social networks (Lutz et al. 2014). Instead, adolescents tend to perceive exceptionally high demands from disclosure and social pressure (Weinstein and Selman 2016a).

In their efforts to overcome digital stress, individuals activate different coping responses. To account for the differences in coping behavior due to individual (e.g., age, gender, personality) (DeLongis and Holtzman 2005; Eschenbeck et al. 2007) and situational conditions (e.g., major life events, illness, ICT use) (DeLongis and Holtzman 2005; Salo et al. 2017), a context- (ICT use) and population-specific (adolescents) consideration of coping responses is essential.

Nevertheless, only two studies combine both perspectives and investigate <u>adolescents'</u> ways of coping with <u>technostress</u>. The first study examined technostress arising from ICT-enabled social conflicts (but not other technostress creators). It proposed five strategies (*get help from others*, *communicate directly*, *cut ties*, *ignore or avoid the situation*, and *utilize digital solutions*) for coping with socio-digital demands (Weinstein et al. 2016). The other study provided evidence that girls and boys cope differently with stress from internet addiction (Li et al. 2019). While both studies advance knowledge on adolescents' technostress coping, they considered only a small selection of technostress creators and did not yet explore adolescents' specific coping responses to multiple technostress creators.

Extending the view to <u>other populations</u>, various studies have shed light on how individuals cope with <u>technostress</u>. To present an overview of existing literature on digital stress coping, these studies have already been presented in section 2.3, concluding that additional efforts are required. This study here aims to identify specific coping responses and typifies them according to two of the presented articles: First, it uses the three types of control (method control, resource control, and timing control) presented by Galluch et al. (2015) to describe the coping responses' effects. Second, it embeds them into the framework from Salo et al. (2017), distinguishing five technostress intervention types (modification of ICT features, modification of ICT use routines, modification of personal reactions to ICT stressors, temporary disengagement from ICT, and online and offline venting).

The literature on <u>stress</u> (other than technostress) coping by <u>adolescents</u> brings in another perspective. It strives to understand what adolescents can do against stress to protect them from suffering from the outcomes of high stress and ineffective coping despite having limited capabilities for coping (Compas et al. 2001). Various studies aimed to grasp how adolescents can effectively mitigate stress and produced an informative and largely congruent portfolio of coping strategies that adolescents can pursue: The strategy *distraction/recreation* involves responses that help regulate emotions and restore or maintain emotional resources (de Anda et al. 2000; Hampel et al. 2018; Zimmer-Gembeck and Skinner 2011). *Cognitive control* refers to cognitive efforts that help maintain control over one's resources (e.g., re-evaluating the situation or giving positive self-instruction) (de Anda et al. 2000). While adolescents who pursue the strategy of *rumination/venting* cannot stop thinking about the stressful situation and frequently talk about consequential feelings, *denial* refers to the opposite case in which individuals disclaim that they have stress (Carver et al. 1989; Hampel et al. 2018). Seeking support can help stressed individuals in two ways: *seeking emotional support* can mitigate the emotional rebound and is an emotion-focused way of coping, whereas *seeking instrumental support* aids in reducing the problem through assistance, information, or materials (Carver et al. 1989; Carver 1997; de Anda et al. 2000; Hampel et al. 2018; Zimmer-Gembeck and Skinner 2011). Further problem-focused ways of coping are *situation control*, which comprises all efforts that aim to obtain control over the problem, and *confrontation/aggression*, which corresponds to approaching the cause for social stress (de Anda et al. 2000; Hampel et al. 2018). Several studies emphasize that family can play a crucial role in conveying essential coping abilities and facilitating adequate coping responses (Shulman et al. 1987). Although stress coping literature has produced a rich list of coping responses activated by adolescents to mitigate stress, most of these studies stem from a time where ICT use was far less common. Therefore, it is not clear to what extent they transfer to technostress.

Methodology

Our mixed-methods approach pursues a developmental purpose (Venkatesh et al. 2013) to approach the two research questions and contribute to a better understanding of how adolescents cope with technostress. We employ a sequential design with first a qualitative study (Study 1) and then a quantitative study (Study 2) (Venkatesh et al. 2016). In this mix, the quantitative study is dominant (Venkatesh et al. 2016).

Study 1 expands existing knowledge on technostress coping by developing a list of coping responses adolescents activate to mitigate technostress based on qualitative data collected in workshops with three school classes. Study 2 employs a structured online survey and quantitative analysis to collect empirical evidence for the activation of the coping responses from Study 1, evaluate patterns in adolescents' coping behavior with individual and situational parameters, and identify factors underlying adolescents' selection of coping responses. The following subsections describe the methodology used in Study 1 and Study 2 in detail.

Both studies collected data in German secondary schools with the explicit consent of the school principals and the supervising teachers. We provided focused information on the study for parents to ensure compliance with ethical requirements in research with adolescents (Levine 2008). Neither of both studies puts the adolescents at risk beyond the risks of a typical school lesson. The adolescents' participation was voluntary for the in-class sessions in both studies and the survey in study 2. We informed them about the purpose of the research, and that aggregate results would be published. We collected data anonymously and did not grant any incentives for participation. Adolescents had the opportunity to raise concerns with us, their teacher, or the school management and/or leave the classroom for the in-class sessions. None of the adolescents did so. Participation in the survey was not mandatory but announced as voluntary homework.

Study 1: Qualitative Workshops

Methods

In Study 1, we carried out interactive workshops with three classes in two mixed German secondary schools to compile a rich collection of technostress coping responses for subsequent quantitative analysis while at the same time providing educational and informative benefits to the participating adolescents. Workshops have been introduced as a valid way of collecting qualitative data (Ørngreen and Levinsen 2017; Shaw 2006), which emerge in a collaborative, creative process (Ørngreen and Levinsen 2017) and satisfy typical evaluation criteria for qualitative research (Guba and Lincoln 1989; Shaw 2006). We integrated the workshops into regular school lessons to create a familiar and safe environment where adolescents can speak freely without fear of negative consequences arising from their participation (Levine 2008; Ørngreen and Levinsen 2017).

A total of 75 adolescents took part in Study 1. We interacted with one seventh grade (27 adolescents aged 12 to 13) in an intermediate secondary school and two eleventh grades (48 adolescents aged 16 to 17) in a higher educational secondary school. In all school classes, about half of the participants were female. Each workshop took 90 minutes and consisted of two parts of approximately equal length. All workshops were led by the same researcher who tried to stick to similar words across the workshops. In the first part, the researcher and adolescents jointly worked on establishing a basic understanding of technostress. The second part focused on technostress coping and collected coping responses that adolescents can activate to mitigate technostress.

The first part began with the researcher giving a short introduction to the concepts of stress and technostress, followed by an explanation of the eight technostress creators presented in the Theoretical Foundations subsection. While describing the technostress creators to the adolescents bears the risk of biasing the results to some extent, prior discussions with adolescents and schoolteachers suggested that reflection on ICT usage and technostress might only be marginal and, thus, basic information triggering reflection on one's behavior is advisable. Although most, if not all, adolescents had already experienced technostress, the theoretical concepts are likely new to them. To prevent them from getting stuck to the researchers' words, we did not provide specific examples for the technostress creators. Instead, we encouraged the adolescents to think about situations in which they or friends experienced each technostress creator and share their examples with the class. The researchers noted all examples given by the adolescents on the blackboard to be visible for the class throughout the workshop. After collecting examples for each technostress creator and having a short break, the second part introduced the concept of coping (Lazarus and Folkman 1984; Salo et al. 2017). Again, we did not provide specific examples of coping responses and refrained from evaluating coping as per se good or bad. Instead, we asked the adolescents to get together in groups of three and discuss what coping responses can help mitigate technostress. Within the group work of 15 minutes, the adolescents were invited to remember or imagine situations in which they or friends felt or might feel techno-stressed and to reflect which coping responses were or could have been applied. Subsequently, each group presented their results to the class, and we recorded all potential coping responses mentioned by the adolescents on the blackboard. At the end of the groups' presentations, we photographed the blackboard and asked the adolescents to share the notes made during the group work with us voluntarily.

The workshops' procedure took care of data credibility and data confirmability (Guba and Lincoln 1989) by producing knowledge shared by the group (Shaw 2006) that can be verified in future research. While the working instructions given to the adolescents might have also evoked the nomination of hypothetical but not personally tested coping responses, we argue that this open formulation is indispensable in our setting as it allows adolescents to cover their own experiences and talk openly without having to disclose personal feelings, experiences, and behaviors (Levine 2008). Similarly, we refrain from taping and transcribing the workshops to maintain privacy in the sensitive group of adolescents (Levine 2008). Instead, we collected the blackboard photographs and the notes from group work as field notes (Miles and Huberman 1994), which are a valid source of qualitative data in workshops (Ørngreen and Levinsen 2017). We do not infer frequent activation of the coping responses directly from the qualitative analysis but perform subsequent quantitative analysis with an anonymous survey. The consistent workshop structure producing similar results in the three school classes suggests the results' dependability (Guba and Lincoln 1989). The detailed description here provides the basis for the results' transferability to other contexts (Guba and Lincoln 1989).

Data Analysis and Results

The adolescents participating in Study 1 suggested 36 coping responses. We grouped them into five categories of theoretically similar coping responses based on content-wise similarities and their anchoring in theory. In a card sorting, nine IS scholars familiar with technostress and coping assigned each of the initial coping responses to one of the categories and achieved a substantial level of agreement between the judges based on a Fleiss' Kappa of 0.680 (Landis and Koch 1977). As an aggregate outcome, we assigned a coping response to a category if more than half (five or more) of the judges assigned it to the category. A hit ratio, that is, the level of agreement between the judges' and our prior categorization, of .910 serves as evidence for construct validity. Several judges suggested to group highly related coping responses into broader concepts and to define some coping responses more abstractly.[6] This grouping reduced the initial list of 36 coping responses to 30 (Table 14). The list of coping responses fulfills the developmental purpose in our mixed-methods design and informs Study 2 for subsequent quantitative data collection and analysis.

[6] Following the judges' suggestions, we merged the coping responses *listen to music*, *read a book*, and *go for a walk* to the new coping response <u>*distract oneself*</u> (*E3*), combined *family activities* and *meet with friends* to <u>*engage in activities with family and friends*</u> (*E2*), generalized *gather information*, *introspect*, and *build up awareness* to <u>*educate oneself on how to prevent TS*</u>, and abstracted *activate blue filter* to <u>*prevent sleep disturbances by ICT*</u> (*T5*).

ID	Coping responses suggested by adolescents	Category	Theoretical anchoring
E1	Talk with others about own TS perception	Emotion regulation	Responses that help the individual feel better emotionally. Emotion regulation corresponds to the technostress intervention action field *recovery from strain* (Salo et al. 2017) and includes various emotion-focused coping responses (*distraction*, *recreation*, *rumination/venting*, *seeking emotional support*, and partially *cognitive control*) (de Anda et al. 2000; Hampel et al. 2018).
E2	Engage in activities with family and friends		
E3	Distract oneself		
E4	Sleep more than usual		
E5	Talk oneself into believing to have no TS		
E6	Seek professional help		
K1	Respect parents' advice on how to use ICT	Knowledge acquisition	Actions to collect information and acquire knowledge that helps individuals to actively reduce current technostress and prevent future technostress. Coping responses in this category aim to obtain *control over one's own cognition* (de Anda et al. 2000), often draw from *instrumental social support* (Carver 1997; Hampel et al. 2018), *modify the personal reactions to ICT stressors* (Salo et al. 2017), and pave the way for targeted problem-focused coping.
K2	Educate oneself on how to prevent TS		
K3	Read privacy policies		
K4	Remember school advice on how to use ICT		
K5	Take time to learn how to use new ICT		
K6	Try to understand what causes TS in oneself		
B1	Discontinue use of specific ICT	Behavior adaptation	Conscious changes in behavior when using ICT in order to reduce the problem and better be able to control the situation (Hampel et al. 2018). Behavior adaptation corresponds to a *modification of IT use routines* intervention (Salo et al. 2017) and exerts *method control* and *resource control* (Galluch et al. 2015). Examples include discontinuing the use of a specific ICT or leaving the smartphone at home when meeting friends.
B2	Avoid aggressiveness in ICT		
B3	Limit oneself to a single device		
B4	Leave the smartphone at home		
B5	Seek personal contact		
B6	Select social networks carefully		
T1	Delete social network accounts	Technology adaptation	Similarly to behavioral actions, technological actions help individuals improve situational control (Hampel et al. 2018) but, in contrast to behavioral actions, *modify the IT features* (e.g., by activating the flight mode or muting crowded chat groups) instead of altering the individuals' use of ICT (Salo et al. 2017).
T2	Adjust privacy settings		
T3	Mute chat groups		
T4	Activate silent or flight mode		
T5	Prevent sleep disturbances by ICT		
T6	Remove unneeded apps or files		
R1	Follow parents' time restrictions for ICT use	Social rules	Social rules are a form of *instrumental social support* (Carver 1997; Hampel et al. 2018) and a precursor of *modified IT use routines* (Salo et al. 2017), which helps adolescents take appropriate measures consciously. Multiple adolescents described compliance with parental and school rules on ICT use as a way of coping with technostress and suggested the establishment of peer rules to mitigate adverse outcomes of ICT use.
R2	Follow parents' rules regarding ICT content		
R3	Follow parents' device rules for ICT use		
R4	Buy ICT on one's own		
R5	Make rules with friends about ICT use		
R6	Follow school rules for ICT use		

Table 14: List of Coping Responses as Output of Study 1 and Input to Study 2

We find that the coping responses collected in the workshops mostly relate to extant research on adolescents' stress coping or individuals' technostress coping but tend to be more specific and actionable. For example, the coping responses in our dataset describe several ways of seeking *distraction/recreation* (de Anda et al. 2000; Hampel et al. 2018; Tarafdar et al. 2020) (as a common coping strategy of adolescents (Zimmer-Gembeck and Skinner 2011); e.g., *engage in activities with family and friends* (*E2*), *sleep more than usual* (*E4*), and *distract oneself* (*E3*)) or *modifying one's IT use routines* (Salo et al. 2017) (as an individual's intervention strategy to mitigate their technostress; e.g., *discontinue use of specific ICT* (*B1*), *leave the smartphone at home* (*B4*), and *seek personal contact* (*B5*)). What is remarkable is that the adolescents in our study reported many problem-focused but few emotion-focused coping responses (all of which have been assigned to the *Emotion Regulation* category). A possible explanation for this is that adolescents might feel familiar with using ICT and, thus, perceive technostress creators as easier to approach than other causes of stress (e.g., social stressors). Another observation is that parental and school rules play a major role in adolescents' coping behavior. Although adherence to social rules can be regarded rather as a catalyst for subsequent coping (Shulman et al. 1987) than as a conscious coping decision, rules might directly or indirectly influence the outcome of technostress reactions and determine adolescents' behavior associated with ICT. While *seeking instrumental support* is a known way adolescents use to cope with stress, the acquisition of ICT-related knowledge and skills seems to be of particular relevance to their coping with technostress. Exemplary coping responses are *educate oneself on how to prevent technostress* (*K2*) or *take time to learn how to use new ICT* (*K5*).

Study 2: Quantitative Survey

Methods

Study 2 investigates 1) how frequently adolescents activate the 30 coping responses from Study 1, 2) how the selection of coping responses relates to individual and situational characteristics, and 3) what factors might underlie adolescents' activation of coping responses. We collected empirical data on adolescents' technostress perception and coping behavior in three schools in Germany: one higher educational secondary school with grades 5 to 12 and two gender-separated intermediate secondary schools with grades 5 to 10. The school for girls and the higher educational secondary school are in the urban area; the school for boys is in a more rural area. At least one class of each of the grades 5 to 10 (adolescents aged 10 to 17) in the higher educational secondary school and 5 to 9 (adolescents aged 10 to 16) in the intermediate secondary schools participated in the study. Overall, we reached 1,273 adolescents in 52 classes – 26 in the higher educational secondary school and 13 in each of the intermediate secondary schools. We held a 45-minute school lesson for each participating class introducing basic information on technostress and coping. All lessons were held by the same researcher as in Study 1 and pursued the goal to set the adolescents reflecting their ICT use. Unlike in Study 1, the lessons offered less space to collect examples for the technostress creators and did not include the coping group work. At the end of the lessons, we asked the adolescents to participate in the online survey as voluntary homework.

The survey was conducted in German and consisted of three parts: The first part collected demographic data such as the participant's age, grade, gender, school type, and the number of digital devices they own. The second part asked them about the perceived intensity of the eight technostress creators. Where applicable, the items used in this part corresponded to or were inspired by existing items found in the literature. We did not find a satisfactory scale for the technostress creator *Unreliability* and constructed the scale from qualitative findings from prior studies (Fischer and Riedl 2015). Appendix B.1 provides a complete list of the scales, including their source or development. We selected four to six items based on theoretical considerations to trade-off content validity and length for all scales in our survey. Several adaptations to the original items were necessary to correspond to the context of school-aged adolescents and harmonize the wording across the various items (e.g., extend the focus from items focusing only on a specific ICT such as Facebook (Maier et al. 2012)). All items in this part used a five-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree" (2 = "rather disagree," 3 = "neither agree nor disagree," 4 = "rather agree"). The third part of the questionnaire collected information on the activation frequencies of all coping responses from Study 1, grouped by categories. In this part, participants were asked to specify how often they activate a certain coping response when they feel stressed by ICT on a five-point Likert scale from 1 = "Never" to 5 = "Always" (2 = "Rarely", 3 = "Occasionally", 4 = "Often").

To consider that some questions might be challenging to answer, particularly for younger adolescents, only demographic questions were technically mandatory. Participants could skip items they found challenging to answer or end the survey early. We included only datasets in our statistical analyses where a maximum number of three questions on both the technostress and the coping parts remained unanswered. For data analysis, we used the statistical software R and especially its lavaan package. Most technostress creator scales have satisfactory psychometric properties – see Appendix B.1 for a detailed description of the scale evaluation. However, the scales for the technostress creators *Overload* and *Invasion* exhibit low internal consistency and discriminant validity and are excluded from the analyses. This result is surprising since both scales build on scales frequently used to assess technostress in adult populations. Further research might develop new scales specifically for adolescents. All other scales possess satisfactory properties.

Results

1,273 adolescents in 52 school classes attended the lessons and got access to the survey. 351 adolescents responded to our request to take part in the survey (27.6% response rate). After removing incomplete data, 230 complete datasets on technostress creators and coping remain and go into analysis. The large gap between potential and actual participants might be explained by the fact that participation in the study was voluntary. Most participants completed the survey within 10 minutes. Table 15 shows descriptive statistics of the demographics. While the survey asked for both age and grade, our analysis uses grade as a variable for the adolescents' state of development. Both constructs are substantially correlated, and grade exhibits a more uniform distribution (there were few observations of adolescents aged 10 or 17). We also exclude the school type (higher educational vs. intermediate secondary schools) from our analysis as we cannot conclude if significant effects are due to the different educational levels, the gender separation, or the location.

School	Classes visited	Number of adolescents	Grade range	Grade median	Grade mean	Complete responses (coping)
Urban higher educational secondary school	26	677	5-10	8	7.9	147
Urban girls intermediate secondary school	13	301	5-9	8	7.8	30
Rural boys intermediate secondary school	13	295	5-9	7	6.9	53
Overall	52	1,273				230

Table 15: Demographics of the Participants

In the following, we report quantitative analyses of the questionnaire data on technostress creators and coping responses. For these analyses, *gender* is a dichotomous variable, where 1 refers to females (103 adolescents), and 0 refers to males. *Devices* has an ordinal scale, where 1 is used for adolescents that own a maximum of two devices (60 adolescents), 2 for those possessing three or four devices (89), and 3 for those with five or more devices (81). While we report significant differences in the following, they are observations in our sample that need to be further researched.

Results on technostress creators

A prerequisite for understanding adolescents' technostress coping behavior is their perception of technostress. This paragraph gives a short overview of adolescents' technostress experiences in our sample (N = 230); Appendix B.2 provides a detailed description. First, empirical data suggest that technostress is a problem for adolescents, but the overall perceived intensity is, on average, lower than that of adult samples reported in the literature. Second, there are large differences in perceived intensity between the eight technostress creators. While adolescents perceive the highest demands from *Disclosure* (M = 3.04), *Complexity* places the lowest demands on them (M = 1.71). Third, our data indicate that gender differences exist: Girls reported significantly higher levels of overall technostress (M = 2.70) than boys (M = 2.20) based on a Mann-Whitney U test, W = 3678, p < .001, with an effect size of r = 0.37, medium effect. To control for side effects of school form and location, we performed the same test on a subsample with only the adolescents in the urban higher educational school (73 girls, 74 boys) as a robustness check and obtained similar results, W = 2032.5, p < .001, r = 0.39, medium effect. Likewise, each of the six technostress creators is perceived significantly more intensely by girls compared to boys. Fourth, the adolescents' grade allows for a similar but slightly less pronounced observation: adolescents in higher grades report significantly higher levels of all technostress creators except *Complexity* and *Social Pressure*.

Descriptive statistics

Data on the coping responses unveil that many adolescents activate technostress coping responses and that large deviance in frequency between the different coping responses exists. While *remove unneeded apps or files* (*T6*) is the most popular coping response with a mean of 3.70, not surprisingly, *seek professional help* (*E6*) is only the ultima ratio in coping with technostress (M = 1.29). Appendix B.3 shows the activation frequencies of all coping responses from Study 1.

Exploratory factor analysis

To better understand adolescents' coping behavior and provide relevant insights for RQ2, we conduct an exploratory factor analysis (EFA) exploring which factors might underlie adolescents' activation of coping responses. According to parallel analysis (Horn 1965), a five-factor solution captures the variance in the data best. Although these factors partially overlap with the theoretical categorization, they are conceptually independent of the categories described in Study 1. Study 1 aimed to group theoretically similar coping responses; the factor analysis here aims to identify factors that underlie the activation of coping responses empirically. Therefore, we pose that the interpretation of these factors requires a nuanced consideration. Appendix B.4 provides a complete list of the loadings of the coping responses on the factors.

From analyzing these loadings, we find that for four of the factors the coping responses loading on them are highly connected. Although our analysis does not fully grasp the factors' antecedents since coping responses are activated in a complex interplay of individual, situational, and environmental conditions, we identify several behavioral patterns that might guide adolescents' activation of coping responses and name the factors accordingly *Avoid Stressful ICT*, *Follow the Rules*, *Use ICT Consciously*, and *Contain Negative Emotions*. There seems to be a focus on coping responses from a specific theoretical category for each of these factors. The fifth factor has a loading from the coping response *R4* (*Buy ICT on one's own*) and a minor cross-loading with the *Avoid Stressful ICT* factor from *T2* (*Adjust privacy settings*). We name this factor *Acquire ICT* as it seems to relate to the circumstance that adolescents buy ICT independently. The coping responses from the *Behavior adaptation* category do not exhibit an apparent pattern but distribute across three factors.

Relationships of demographic data and coping responses

Subsequent analyses of the coping responses reveal interesting relationships with demographic data on both the coping response and factor levels. While there is no overarching pattern (such as the finding that girls perceive higher technostress than boys for all analyzed technostress creators) for coping, the correlations between the demographic factors and the coping responses seem to be more nuanced and show different patterns across the five factors. Table 16 displays the correlations of the coping responses with demographic data, grouped by factors. We discuss these relationships in the Integrated Results section. For better interpretability of the observations relating to gender, we again performed a robustness check with the urban higher educational subsample and found significant but less pronounced effects. Appendix B.5 presents details on this analysis.

CP	ID	Coping Response	Grade^{s}	Devices^{s}	Gender$^{b,+}$
Avoid Stressful ICT	E2	Engage in activities with family and friends	**.137***	**-.251*****	**.185****
	E3	Distract oneself	.093	**-.210****	**.301*****
	B5	Seek personal contact	**.215****	**-.213****	**.265*****
	B6	Select social networks carefully	**.177****	-.093	**.182****
	T2	Adjust privacy settings	.106	-.073	**.234*****
	T3	Mute chat groups	**.182****	-.073	**.182****
	T4	Activate silent or flight mode	**.230*****	-.068	**.225*****
	T5	Prevent sleep disturbances by ICT	**.176****	**-.163***	**.207****
	T6	Remove unneeded apps or files	**.145***	-.088	**.140***
Follow the Rules	R1	Follow parents' time restrictions for ICT use	**-.155***	**-.258*****	-.039
	R2	Follow parents' rules regarding ICT content	**-.202****	**-.234*****	-.102
	R3	Follow parents' rules regarding device use	-.106	**-.259*****	.006
	R6	Follow school rules for ICT use	**-.167***	**-.217*****	.009
	K1	Respect parents' advice on how to use ICT	-.072	**-.271*****	.004
	B4	Leave the smartphone at home	-.110	**-.134***	.017
Use ICT Consciously	K2	Educate oneself on how to prevent TS	-.070	-.045	**-.133***
	K3	Read privacy policies	**-.206****	**-.138***	-.004
	K4	Remember school advice on how to use ICT	-.089	**-.177****	.072
	K5	Take time to learn how to use new ICT	.075	-.082	**-.149***
	K6	Try to understand what causes TS in oneself	-.006	**-.231*****	.090
Contain Negative Emotions	E4	Sleep more than usual	**.214****	.017	**.181****
	E5	Talk oneself into believing to have no TS	**.191****	.039	**.248*****
	E6	Seek professional help	**-.192****	-.043	-.094
	B1	Discontinue use of specific ICT	.083	**-.160***	**.211****
	B3	Limit oneself to a single device	.064	**-.227*****	**.232*****
	R5	Make rules with friends about ICT use	.115	-.076	.101
Acquire ICT	R4	Buy ICT on one's own	**.224*****	.083	-.048
No sig. loadings	T1	Delete social network accounts	.005	-.067	.059
	E1	Talk with others about own TS perception	-.079	**-.273*****	.070
	B2	Avoid aggressiveness in ICT	**.132***	**-.175****	**.224*****

Notes: Significance codes: *** = p < .001, ** = p < .01, * = p < .05
^{s} Spearman correlations, ^{b} point-biserial correlations,
$^{+}$ Appendix B.5 presents a robustness check of gender results

Table 16: Correlations of Coping Responses with Demographic Data, Sorted by Mean Activation Frequency

Relationships of technostress creators and coping responses

In a final step, we relate the coping responses to specific technostress creators. This analysis assumes that individual differences cannot fully explain disparities in adolescents' activation of coping responses and that a situational component depending on which technostress creators the adolescent perceives as taxing might be meaningful. For this purpose, we link each participant's responses on the technostress perception and coping parts of the questionnaire and investigate correlations between both. Our analysis aims to unravel differences in the activation frequency of a specific coping response at low and at high levels of a specific technostress creator compared to medium levels. More specifically, we compare the mean activation frequency of a coping response among participants within the lower or upper quartile of perceived demands from a technostress creator with the coping response's mean activation frequency among participants in the second and third quartile of the technostress creators (middle 50 %). For this comparison, we calculate a ratio q between the lower (or upper) and the middle quartiles, which can be interpreted as follows: A value of q below 0.9 indicates that the coping response is less frequently used in the upper or lower quartile and is represented by the symbol "--" in Table 17. Accordingly, "-" refers to values $0.9 \leq q < 0.95$, "o" to values $0.95 \leq q \leq 1.05$, "+" to values $1.05 < q \leq 1.10$, and "++" to values $q > 1.10$. These thresholds reflect that the technostress creator is one determinant of adolescents' activation of coping responses but not the only one and trade-off broad coverage and explanatory power. Table 17 uses color-coding explained in the table's notes to visualize relations.

Integrated Results: Factors Underlying Coping Behavior

The exploratory factor analysis in Study 2 examined underlying factors in adolescents' activation of the 30 coping responses adopted from Study 1. Five factors emerged from this analysis and painted a clearer picture of adolescents' coping behavior in response to technostress. This subsection provides details on the factors, investigates their theoretical underpinning with the categories from Study 1, interrelates both studies' results, and examines their relationships with demographic data and technostress creators. However, it is important to note that from the statistical relationship between technostress creators and coping responses in our cross-sectional quantitative data, one cannot deduce causality because stress appraisal and coping affect each other (Salo et al. 2020).

Avoid Stressful ICT

Five of six coping responses from the *Technology adaptation* category and two from each of the *Emotion regulation* and the *Behavior adaptation* categories load high on the *Avoid Stressful ICT* factor. A closer look at these coping responses reveals that the factor seemingly relates to avoidant behavior, either by escaping from ICT in general (e.g., *Engage in activities with family and friends* (*E2*) or *Seek personal contact* (*B5*)) or by avoiding ICT and ICT characteristics creating stress (e.g., *Select social networks carefully* (*B6*) or *Mute chat groups* (*T3*)). It anchors in technostress coping literature as *controlling the situation* (Hampel et al. 2018) through *modifying their use of ICT* or *modifying the IT features* (Salo et al. 2017). The coping responses loading on *Avoid Stressful ICT* are activated frequently (M = 3.28) with all mean activation frequencies (min. M = 2.76, max. M = 3.70) lying above the average across all coping responses (M = 2.71). Hence, the *Avoid Stressful ICT* factor describes a pattern most adolescents access.

CP	ID	Coping Response	Disclosure Low / High	Unreliability Low / High	Uncertainty Low / High	Insecurity Low / High	Soc. Pressure Low / High	Complexity Low / High
Avoid Stressful ICT	E2	Engage in activities with family and friends	-- / o	-- / o	-- / ++	- / ++	-- / ++	-- / ++
	E3	Distract oneself	-- / o	-- / o	-- / ++	- / ++	-- / o	- / o
	B5	Seek personal contact	-- / o	-- / ++	- / ++	o / ++	-- / ++	-- / o
	B6	Select social networks carefully	-- / o	-- / o	-- / o	-- / o	-- / o	-- / o
	T2	Adjust privacy settings	-- / o	-- / o	-- / o	-- / ++	-- / ++	-- / o
	T3	Mute chat groups	-- / o	-- / o	-- / ++	-- / ++	-- / ++	-- / o
	T4	Activate silent or flight mode	-- / ++	-- / o	-- / ++	-- / ++	-- / o	-- / o
	T5	Prevent sleep disturbances by ICT	-- / o	+ / ++	-- / o	o / ++	-- / ++	-- / o
	T6	Remove unneeded apps or files	-- / ++	- / o	- / o	-- / ++	-- / o	-- / o
Follow the Rules	R1	Follow parents' time restrictions for ICT use	- / o	+ / ++	o / o	- / o	- / -	-- / ++
	R2	Follow parents' rules regarding ICT content	o / o	++ / ++	++ / ++	- / o	-- / --	- / ++
	R3	Follow parents' rules regarding device use	o / o	+ / o	+ / o	- / o	-- / -	-- / o
	R6	Follow school rules for ICT use	o / o	o / o	o / o	-- / o	-- / -	-- / o
	K1	Respect parents' advice on how to use ICT	-- / o	o / o	o / o	-- / o	o / ++	-- / ++
	B4	Leave the smartphone at home	-- / o	++ / ++	+ / o	-- / o	- / ++	-- / ++
Use ICT Consciously	K2	Educate oneself on how to prevent TS	-- / o	++ / o	- / -	-- / o	- / --	- / o
	K3	Read privacy policies	o / o	++ / o	+ / ++	-- / -	o / o	o / ++
	K4	Remember school advice on how to use ICT	- / -	- / o	+ / ++	-- / -	-- / o	-- / o
	K5	Take time to learn how to use new ICT	- / -	o / o	++ / o	-- / o	-- / o	o / o
	K6	Try to understand what causes TS in oneself	-- / o	o / o	- / ++	-- / ++	-- / ++	- / ++
Contain Negative Emotions	E4	Sleep more than usual	-- / ++	-- / o	-- / o	-- / o	-- / ++	- / ++
	E5	Talk oneself into believing to have no TS	-- / ++	-- / o	-- / o	-- / ++	o / ++	- / ++
	E6	Seek professional help	- / -	++ / o	o / --	-- / -	+ / ++	++ / ++
	B1	Discontinue use of specific ICT	-- / o	- / ++	-- / ++	- / ++	-- / o	-- / o
	B3	Limit oneself to a single device	-- / o	-- / ++	-- / ++	-- / o	- / ++	-- / ++
	R5	Make rules with friends about ICT use	-- / o	-- / -	-- / o	-- / o	o / ++	-- / o
Acquire ICT	R4	Buy ICT on one's own	o / o	-- / -	o / -	-- / o	-- / o	o / o
No sig. loadings	T1	Delete social network accounts	-- / o	++ / ++	-- / o	-- / ++	-- / ++	-- / ++
	E1	Talk with others about own TS perception	o / --	o / o	-- / o	-- / -	- / o	-- / o
	B2	Avoid aggressiveness in ICT	-- / o	o / o	o / ++	-- / ++	-- / ++	o / ++

Notes: Color coding:
grey = positive relationship (increasing activation with increasing technostress creator intensity);
yellow = lower application in the high segment;
green = higher application in the low segment;
white = marginal differences in low and high segments

Table 17: Relationships of Coping Responses and Technostress Creators

It has the distinctive feature that all coping responses significantly relate to the adolescents' genders. Looking at the unweighted average of the coping responses loading on the *Avoid Stressful ICT* factor, girls (M = 3.60) activate them significantly more often than boys (M = 3.02), Mann-Whitney U test, W = 3820, p < .001, with an effect size of r = 0.36, medium effect. While this observation might obscure possible side effects arising from the school form and location, we find a similar but less pronounced pattern also in the subsample comprising only the girls and boys at the urban higher educational secondary school, W = 1790, p < .001, r = .29, low effect. The finding that girls show higher degrees of avoidant behavior is consistent with the literature (Ptacek et al. 1994; Taylor et al. 2000) and might be explained by the fact that the girls in our study tend to perceive more technostress than the boys. Further, seven of the nine coping responses show significant correlations with the adolescents' grade. A regression model investigating the linear relationship between the adolescents' mean activation frequency of coping responses with their grade reveals that escape-avoidance behavior seems to increase significantly with the grade, b = 0.14, t(228) = 4.34, p < .001, and that grade explains a significant proportion of variance in the mean activation frequency of escape-avoidance coping responses, R^2 = .08, F(1,228) = 18.83.

Follow the Rules

The *Follow the Rules* factor takes its name from the perception that all coping responses loading on this factor relate to behavior that is considered conscientious. These coping responses include four *Social rules* plus the two coping responses *Respect parents' advice on how to use ICT* (*K1*) and *Leave the smartphone at home* (*B4*). They relate to information, guidelines, or rules typically provided or imposed by a third party such as parents (*R1-3*, *K1*, *B4*) or school (*R6*, *B4*). Hence, we assume that adolescents with a high degree of conscientiousness resort to *Follow the Rules* coping. Adolescents showing this behavior utilize *instrumental social support* (Carver 1997; Hampel et al. 2018) to facilitate a *modification of IT use routines* (Salo et al. 2017). Of all coping responses loading on the factor, the activity *follow school rules for ICT use* (*R6*) ranks highest with a mean of 3.62. This ranking is not surprising because German schools have a general ban on mobile phone use and penalize adolescents if their device is turned on. Conversely, fewer adolescents *leave the smartphone at home* (*B4*, M = 2.43), making it the least frequently activated coping response associated with the *Follow the Rules* factor (M = 2.99).

The factor exhibits various interesting relationships with demographic data. First, three of the four coping responses loading on this factor are significantly related to the school grade. A closer look reveals that adolescents in the fifth and sixth grades have a high tendency to comply with rules (M = 3.47), but compliance drops with the grade level (M = 2.80 for grades 7 to 10). The decline in the seventh grade allows for multiple interpretations. In our qualitative inquiry, several seventh graders mentioned that their parents have recently loosened the rules regarding their ICT use. The reduced activation frequency of rules could thus be due to a lower number of imposed rules. Also, adolescents come into the age of puberty and tend to rebel against supervisors, resulting in lower compliance with rules. Finally, we find a negative relationship between the number of devices an adolescent owns and their compliance with rules. This observation manifests in significant correlations for all coping responses loading on the *Follow the Rules* factor. A comparison of the means reveals that there is a significant difference between the three groups "two or less devices" (M = 3.49, N = 60), "three or four devices" (M = 2.94, N = 89), and "more than four devices" (M = 2.66, N = 81) based on a regression model, b = -0.41, t(228) = -4.873, p < .001, with an explanatory power of R^2 = .09, F(1, 228) = 23.75. Again, this can be read in various ways: the possession of more devices might indicate either that parents impose fewer restrictions or that adolescents have a higher tendency to ignore these rules the more devices they have in reach.

In the *Follow the Rules* factor, there is low variance in the activation frequency for high values of *Disclosure*, *Uncertainty*, and *Insecurity*, indicating that adolescents' compliance with rules seems to be independent of specific issues with one of these technostress creators. Considering that adolescents likely follow the rules because they must and not because they appreciate their parents' technological competence, this insight is not surprising. Additionally, we find that adolescents who perceive either high or low intensity of *Social Pressure* tend to activate the *Social rules* coping responses related to this factor less frequently than the reference group. A possible explanation could be that adolescents perceiving high pressure from their peers might tend to ignore parental rules to meet their peers' expectations. Likewise, those who perceive low social pressure do not feel pressured by their parents' rules either. Contrary, adolescents apply parental rules more often when *Unreliability* is either low or high. While there is no obvious explanation for this observation, it suggests that high and low compliance with rules might relate to more confident ICT use.

Use ICT Consciously

The *Use ICT Consciously* factor has high loadings of five of the six coping responses from the *Knowledge Acquisition* category. It is the only factor that relates exclusively to coping responses from one category. The theoretical anchoring suggests that conscious ICT use implements the *modification of personal reactions to ICT stressors* (Salo et al. 2017), mainly by *maintaining cognitive control* (de Anda et al. 2000) or by *using instrumental support* (Carver 1997; Hampel et al. 2018). Three of the five coping responses have a significant negative association with the number of owned devices. This also manifests when investigating the relationship between the mean across all related coping responses (M = 2.25) and the number of devices in a linear regression, b = -0.18, $t(228)$ = -2.681, p = .008, R^2 = .03, $F(1, 228)$. A possible explanation might be that the more devices an adolescent owns, the less effort they put into reflecting their ICT use. Further, conscious ICT use seems to be rather independent of high perceptions of *Unreliability* and largely also of *Disclosure*. Apart from that, the specific shaping of this factor seems to be more nuanced. Altogether, these findings indicate that the differences in the activation of coping responses associated with the *Knowledge acquisition* factor cannot be consistently explained by the individual and situational characteristics investigated in our study. Here, further analysis is needed.

Contain Negative Emotions

From the five factors emerging from the EFA, the *Contain Negative Emotions* appears to be the most heterogeneous. While three of the six associated coping responses belong to the *Emotion regulation* category, the other three seem to be divergent. We find that the largest bracket encompassing the coping responses loading on this factor is the containment of negative emotions, e.g., by sleeping (*E4*), self-calming (*E5*), or *Seeking professional help* (*E6*). However, the connection is less apparent for the other three coping responses. All six coping responses have in common that their distribution is left-skewed and that the mean activation frequencies (min. M = 1.28, max. M = 2.59, mean M = 2.10) are below the overall average (M = 2.71). The finding that the directions of correlations vary across the coping responses for all three demographic variables adds to the impression of heterogeneity. Therefore, we pose that the investigation of significant relationships for this factor does not produce valuable insights.

Acquire ICT

Lastly, the factor *Acquire ICT* is dominated by a high loading of *Buy ICT on one's own* (*R4*) and has a minor loading of *T2*. *R4* significantly correlates with grade and seems independent of *Disclosure* and *Complexity*, but there is no consistent pattern across both coping responses.

Discussion

Our mixed-methods design strived to understand adolescents' technostress coping behavior. The results of a qualitative and a quantitative study shed light upon adolescents' technostress coping and pave the way for subsequent research in the field of technostress coping. We draw several interesting inferences from each of the two studies. Combining the two studies produces a rich set of meta-inferences which is an important benefit of mixed-methods research (Venkatesh et al. 2013). Table 18 summarizes the study's meta-inferences.

Qualitative Inference	Quantitative Inference	Meta-inference	Reasoning
Adolescents draw from a broad range of coping responses to mitigate technostress.	Adolescents apply almost all coping responses, but their activation frequencies differ.	While adolescents as a group have a broad range of coping responses, not all coping responses are equally relevant to their coping with technostress.	The multi-faceted nature of technostress, along with individual, environmental, and situational differences, allows for a multi-faceted approach to technostress coping.
Some coping responses target specific technostress creators; some are perceived as effective on multiple technostress creators.	Gender and grade (related to age) play a role in the activation of coping responses. While heavy use of coping responses generally goes along with higher levels of technostress, some coping responses seem to particularly relate to specific technostress creators.	Which coping responses an adolescent activates is associated with both individual and situational factors.	Both the individual and the situational factors in part change with adolescents‘ development.
Adolescents' technostress coping responses can be classified into different theoretical categories.	Different factors underlie the activation of technostress coping responses by adolescents.	Adolescents' technostress coping behavior relates to factors that align with the theoretical category, indicating the existence of different coping styles.	Adolescents might be limited in knowledge and ability or might possess heterogeneous preferences regarding technostress coping.

Table 18: Qualitative Inferences, Quantitative Inferences, and Meta-Inferences

Thirty coping responses emerged from Study 1 based on adolescents' qualitative testimonies in group work. A partitioning into five theoretical categories suggested that they cover a broad spectrum of coping responses ranging from activities supporting emotion regulation to problem-oriented responses like adaptations of ICT and their use. In Study 2, we collected empirical evidence that adolescents activate almost all coping responses adopted from Study 1 frequently (except for *Seek professional help* (*E6*), *M = 1.28*), but different factors determine adolescents' activation of coping responses. Also, the activation of coping responses seems to be associated with individual and situational parameters. This inference is based on exploratory factor analysis that yields five factors underlying adolescents' activation of coping responses in our sample. For four of these factors, the coping responses loading on them pursue similar purposes and largely overlap with one of the theoretical categories from Study 1. This finding indicates that underlying behavioral patterns shift adolescents to the activation of similar coping responses. However, the literature suggests that at least a combination of emotion-focused and problem-focused coping responses works best to mitigate technostress (Beaudry and Pinsonneault 2005).

Theoretical Contributions

Our research elaborated on two research questions: First, we aimed to gain an overview of coping responses that adolescents activate to mitigate technostress. Second, we strived for a broader understanding of what determines adolescents' selection of technostress coping responses. The inferences and meta-inferences obtained from analyzing the research questions in two sequential studies contribute to theory in multiple ways.

First, based on extant knowledge on technostress and coping (specifically on technostress coping by adults and on stress coping by adolescents) and qualitative testimonies from adolescents aged 10 to 17, we advanced knowledge of technostress coping by adolescents. This knowledge consists of five theoretical categories with 30 coping responses that adolescents can activate to mitigate technostress. The empirically developed coping responses are mainly in line with research on adolescents' coping with everyday stress (de Anda et al. 2000; Hampel et al. 2018). While, to date, research on adolescents' technostress coping has investigated coping responses to single demands in adolescents' ICT use (Li et al. 2019; Weinstein et al. 2016), our research complements these studies by examining coping with more technostress creators. Further, it complements these studies by providing a wide-ranging, theoretically elicited, and empirically supported set of technostress coping responses for adolescents.

Second, the broad investigation of technostress coping responses by adolescents contributes to developing a comprehensive classification of technostress coping responses (Weinert 2018) and stimulates further examination of differences in technostress coping behavior between adolescent and adult populations. Although our study focused on adolescents who have been underrepresented in technostress research so far, the coping responses embed and detail an existing framework on technostress coping with leisure ICT (Salo et al. 2017) for the specific context of adolescents' ICT use. While some coping responses are rather specific to adolescents (e.g., parental or school rules), various coping responses in our set have already been explored and verified for adults (e.g., *Discontinue use of specific IT* (*B1*) (Maier et al. 2015b) and *Distract oneself* (*E3*) (Tarafdar et al. 2020)). Future research can build on this and explore which coping responses generalize to other populations and what additional coping responses other populations activate.

Third, based on exploratory factor analysis, we derive factors underlying the activation of technostress coping responses. In part, these factors align with the theoretical categorization of coping responses, yet they are conceptually different and novel to technostress coping literature. They are interesting as they point to a better understanding of the diversity in technostress coping. Future research should aim for theoretically grounding and confirming this exploratory result.

Fourth, similarly to prior research (Ayyagari et al. 2011; DeLongis and Holtzman 2005; Eschenbeck et al. 2007; Salo et al. 2017; Tarafdar et al. 2019), we observed that individual differences in the perception of technostress and the activation of coping responses exist. Therefore, the question emerges what the individual, environmental, and situational antecedents of these factors are. We provided a first analysis in this direction by investigating the effect of demographics and technostress creators and found that these parameters partially explain adolescents' coping behavior. For a complete picture, more parameters need to be considered. Hence, future research should explore further antecedents of technostress coping and test if, for example, individual preferences, individual capabilities, environmental conditions, and further situational characteristics play a role.

Overall, our findings advance the theoretical understanding of technostress mitigation measures and contribute to interdisciplinary research on digitalization's dark sides (Ragu-Nathan et al. 2008; Turel et al. 2019; Turel 2019; Weinstein and Selman 2016b). The study responds to recent calls to intensify research on the dark sides of digitalization at the individual level (Turel et al. 2019) and specifically on technostress and technostress coping (Tarafdar et al. 2019; Weinert 2018). It unites different research streams on technostress and illuminates adolescents as a segment of the population that is still underrepresented in technostress research, yet highly relevant, not the least due to the size of the population and their ongoing development and vulnerability.

Practical Implications

While the focus of our work is on theoretical advancement, it also suggests implications for practitioners. Our research may be taken as a reminder for ICT designers and engineers that they have a great responsibility and must factor in the psychological effects associated with the use of their products. We pose that a better understanding of what causes technostress in adolescents can enable ICT producers and providers to create ICTs that are less stressful to use (Tarafdar et al. 2019), for example, by reducing notifications. The same counts for knowledge on effective coping, which could produce innovative ICT designs that support or deliberately leave room for coping with high demands. Our study shows which coping responses innovative ICTs might aim to strengthen. Examples might include content filters that reduce aggressive or disturbing content in ICT (*B2*), assistance systems that provide feedback on emerging technostress (*K6*), and adaptive systems that support individuals in the prevention or mitigation of stressful events, for example, by *preventing sleep disturbances by ICT* (*T5*) or *activating silent or flight mode* (*T4*) automatically.

For parents, teachers, and other adults who shape adolescents' social and technical environment, our results might be valuable to understand the current limitations and theoretical possibilities of adolescents' coping with technostress. Prescriptive knowledge from our mixed-methods study indicates that areas for improvement in adolescents' environment exist. Most importantly, adults may support adolescents in acquiring broader competency in coping with technostress, for example, by training effective coping in school or at home, by providing targeted emotional and instrumental support, or by setting rules on whether, where, when, and how to use different ICT.

Finally, adolescents themselves might find value in our results. Given our experience in discussing technostress and coping with adolescents as part of this research, we do not believe that this paper's presentation is ideal for engaging adolescents in reflection and improvement of their ICT use and coping behavior. Nevertheless, given our experience with in-class discussions, we believe that a target-group-specific presentation of the theoretical knowledge in this paper might support adolescents in reflecting their ICT use, improving it, and becoming more potent at coping with stressful events. We believe that the evidence for differences in coping behavior is, in part, an indication of limited knowledge and ability to leverage the broad set of coping responses available in general – but heterogeneous preferences in coping might also be a factor. Nevertheless, reflection and training might help extend the behavioral toolset for coping with the demands of ICT use individually and in the social context.

Limitations & Future Research

The work at hand has some limitations. First, parts of the research design might have influenced our results. In Study 1, adolescents had the opportunity to cover their own experiences by describing hypothetical coping responses. Further, we did not record the workshops but used field notes as a substitute. The workshops' public format might have limited the nomination of activated coping responses that are not socially desirable. In Study 2, the conduction of workshops before the survey might have biased the results on the technostress questionnaire. Additionally, the results are difficult to interpret for adolescents of the fifth and sixth grades. This difficulty is partly due to a lack of reflection on ICT use and partly due to the lower response rate at that age. A topic for future research is that technostress and technostress coping should be explicitly investigated for such young, and even younger, children.

Second, the observations regarding gender differences and avoidant coping might include side effects with school form and location. Although robustness checks with only the adolescents from the urban higher educational secondary school with a uniform distribution of the two genders allow for similar observations, the differences might be less pronounced than assumed.

Third, internal consistency for the scales of the technostress creators *Invasion* and *Overload* in the measurement model is relatively low, so that these two constructs had to be removed from the analyses. The scales should be further investigated and adapted for future investigations with adolescents. Our data-driven analysis of the interrelation of individual technostress creators and coping responses also allows for more elaborate and theory-driven approaches. Finally, we did neither discuss nor measure the potential positive effects of technostress (eustress) or the psychological and physiological outcomes related to stress and coping.

The following four directions for future research appear promising to extend our findings: First, mitigating technostress for adolescents by shaping their technical environment: In line with other researchers (Tarafdar et al. 2019), we call upon IS scholars to take the perspective of design science research and develop design knowledge for socio-technical systems aware of the user's stress (Adam et al. 2017) and assist them in coping with high demands. Examples could be providing feedback on stress perception, training and expanding coping abilities, or performing automatic actions that help individuals cope. Our insights regarding adolescents' specific coping responses might support this.

Second, mitigating technostress for adolescents by shaping their social environment: Scholars may aim to analyze and design strategies and tactics for individual and collective ICT use and social support for adolescents experiencing technostress. Third, mitigating technostress for adolescents by supporting their skills: Future research should expand on why adolescents cope differently from each other and what individual, environmental, and situational antecedents determine factors in coping behavior. This investigation should also include if, besides knowledge and abilities, heterogeneous preferences might be a reason. Fourth, scholars might use the coping responses, categories, and underlying factors in theorizing on technostress coping at the workplace.

Conclusion

The present paper investigated what coping responses adolescents activate to cope with technostress and what factors underlie their activation of coping responses. We employed a mixed-methods design, starting with a qualitative study and following up on the results with a quantitative study. In the qualitative Study 1, we performed workshops with 75 adolescents in three school classes on their coping responses to technostress. Study 2 used the coping responses identified in the qualitative study for in-depth quantitative analysis. This analysis examined adolescents' self-reported frequency of activating the coping responses adopted from Study 1 based on 230 complete survey responses. It investigated their interrelations with demographic factors and technostress creators and provided evidence for five factors that might underlie adolescents' coping behavior. Jointly, the results of both studies paint an informative picture of adolescents' technostress coping.

5. Designing Information Systems Assisting DTM Users

The third and final perspective of the analysis of individuals' DTM use is the adequate design of DTM (Matt et al. 2019). Informed by behavioral aspects and consequences of DTM use, this perspective aims to deliver DTM that take the users' needs into account and effectively support them. Therefore, this Chapter presents three consecutive studies that pursue the goal to create a mobile assistant supporting individuals' coping with stress. The first study (presented in section 5.1) describes the development and analysis of a mobile prototype using mobile sensors to assess the user's stress. Based on the sensor data and user responses on their perception of stress, an elastic net regression model was created that relates sensor data and stress to estimate the user's current perception of stress. The second study (presented in section 5.2) takes a broader view and proposes a design theory for mobile stress assessment systems. The design theory consists of a design blueprint, design principles, and design features and has been developed based on an analysis of 136 publications on mobile stress assessment and five own prototyping activities. Finally, the third study (presented in section 5.3) extends upon stress assessment and proposes an abstract design of a mobile coping assistant which supports the user in coping with stress by suggesting adequate measures in real-time. Chapter 5 is largely congruent with Gimpel et al. (2019b), Bonenberger et al. (2021), and Schmidt et al. (2022).

5.1. Designing an Information System for Life-Integrated Stress Assessment

One of the most prevalent and discussed health problems of our time is stress (Riedl 2013). Originating from the general rise of complexity and mental load in business and private life, the number of people regularly experiencing stress is increasing (Ferreira et al. 2008). This is an individual and societal, but also an economic problem, as stress can induce unhealthy behavior (e.g., alcohol abuse, smoking) and is the main cause of psychological and physiological illnesses, including burnout (Goh et al. 2015). First efforts towards technological support of stress management and coping have recently been launched in both science (Adam et al. 2017) and practice (Soma Analytics 2019).

This is enabled by today's omnipresence of powerful sensors, for example, in smartphones or smart things, which significantly facilitate access to sensory data. The vast amount of data produced by smartphones' rich sensing capabilities opens the path for sophisticated technological and informational assistance of individuals – a field which is gaining increasing attention in information systems research (Hess et al. 2014; Legner et al. 2017) and contributes to environmental sustainability (Tiefenbeck et al. 2019) and individual health (Lane et al. 2010). In combination with progress in the field of artificial intelligence, this can lay the foundation for IT systems that use sensors and actuators to adapt to the individual user (Dey 2016) in order to serve humanistic (e.g., well-being, health, enjoyment) and instrumental goals (e.g., performance, productivity). Systems focusing on the sensing of psychological parameters such as emotions, well-being, or stress commonly run under the term "affective systems" and provide significant advances in the detection of human affection (Marreiros et al. 2010; Moore et al. 2014). Recent efforts, for example, include intelligent help provision (Friemel et al. 2017), enhancements in personalized healthcare, technological support of health prevention (Nahum-Shani et al. 2018), or the design of stress-sensitive adaptive enterprise systems (Adam et al. 2017).

Resulting artifacts designed to help users dealing with stress range from functionally limited end-user applications that assist in the application of stress management techniques (e.g., the real-time recommendation of appropriate coping mechanisms) to the theoretical conception of enterprise systems that automatically adapt their user interfaces and workflows to the user's cognitive state (Adam et al. 2017). Next evolution steps could be personalized stress-aware user interfaces, safety measures in human-machine interaction, or mobile apps recommending appropriate activities based on the individual's stress level, for example, a relaxing visit to the nearby spa. Systems sensitive to stress require useful input data. However, sensing and evaluation of psychological factors like stress are hard to put into practice: Accurate physiological measurements often require bulky hardware (e.g., electrocardiography) or people's physical presence at a specific location. Thus, they are not applicable for use cases, which require a continuous stream of sensory input, like location-independent adaptive stress interventions.

To overcome these problems, Fischer and Riedl (2019) recently proposed the idea of lifelogging for organizational stress, which suggests that technology can be used to unobtrusively and continuously collect data on an individual and a situation. Various approaches have already emerged that use smartphone data to get information on the user's behavior or environmental context (Lane et al. 2011; Lee et al. 2012; LiKamWa et al. 2013). Although these technology-based approaches are outperformed by physiological measurements regarding quality and accuracy, their broad range of sensors and good integration into people's daily routines can make the assessment of unconscious mental processes widely accessible and applicable (Dimoka et al. 2011). This paves the way for the design of adaptive systems, which continuously sense the individual's mental state and execute regulating measures like adapting the interface or organizational workflows accordingly to better fit the user's needs.

Most use cases call for a fully automated recognition of stress that does not need direct user interaction. However, existing approaches to stress assessment require the user's attention or even collaboration by means of questionnaires or behavior change. In this work, we aim at full life integration of smartphone-based stress assessment without user cooperation and collect real-life evidence for its feasibility. This also excludes the use of wearables such as fitness trackers or smartwatches, which – despite their growing prevalence – for many people still feel unnatural in permanent use and, thus, might not be appropriate for continuous measurement. We follow standard design science research methodology (Hevner et al. 2004; Peffers et al. 2007) to investigate the following design objective:

Design Objective: Design and develop a life-integrated mobile system that is capable to continuously assess a user's stress level without influencing the user's daily habits at all.

The proposed system uses various hardware and software sensors to collect data on both behavior and environmental context associated with common stressors and strains. It is prototypically instantiated and evaluated in a public field study. In comparison to existing prototypes, it does not interfere with the user's perceived routine constraints, such as wearing an unfamiliar device (e.g., wearable) or changing the user's daily routines (e.g., requiring a second smartphone or additional daily actions) (Buchwald et al. 2015). The prototype helps to demonstrate the general feasibility of life-integrated continuous mobile sensing and its generality for the assessment of perceived stress. An analysis of the data gathered within the field study yields a universal stress assessment model, which links data from smartphone sensors to stress valuation and confirms the operationality of life-integrated, continuous, mobile stress assessment. Lessons learned during the development process give valuable insights into the development of stress-sensitive and stress-adaptive systems that respond to the user's stress and provide targeted technological or situational stress management interventions.

This section follows a structure similar to the publication schema suggested by Gregor and Hevner (2013): The subsequent subsection provides background on both the physiological and psychological nature of stress and reviews related work on the mobile sensing of psychological factors. We then shortly outline the research setup and describe the prototype and prototyping process, in which we learned that efficient resource consumption and privacy are even more important for applications that run unobtrusively in the background. The evaluation of data collected within the public field study yields a person-independent classification model that predicts stress as a binary variable with an accuracy of 81 %. A regression model built with the same data distinguishes stress levels between 0 and 16 with a mean absolute error of 2.12 in a cross-validation scenario and explains approximately 41 % of the variance in stress. We further demonstrate that the personalization of the model can significantly improve model accuracy and conclude the section with a discussion of the implications and limitations based on lessons learned during the prototyping and evaluation process, as well as an outlook on future research.

Foundation

Implications from Human Stress Theory

Human stress (section 2.3) is a highly complex and individual phenomenon, which is strongly dependent on the interaction between a person and its environment. Therefore, two aspects are essential to the design of a life-integrated mobile stress assessment system. First, the evaluation, whether a situation is perceived as stressful or not, is performed mentally. Consequently, our system cannot assess the actual stress of a user but must rely on assessable information. Therefore, we require data from sensors that conclude potential stressors (e.g., humidity, noise, number of messages) or strains (e.g., changes in voice, tipping behavior). Second, stress is dependent on the interaction between a person and its environment. Hence, it is necessary to gather information on both the user (e.g., behavioral data) and their environment (e.g., temperature, humidity).

Related Work on Stress Assessment

Today, smartphones are our daily companion. They feature an increasing number of hardware sensors (e.g., air pressure sensor, humidity sensor, and accelerometer) and collect valuable information, which might give an indication about the user’s mental state, as suggested by several researchers. To analyze relevant application scenarios, we conducted an extensive analysis of mobile sensing use cases, which builds on three comprehensive reviews of the literature on mobile stress assessment published by Aigrain (2016), Greene et al. (2016), and Þórarinsdóttir et al. (2017). We complement their list of studies by searching in the AIS Senior Scholars Journal Basket (MISQ, ISR, JAIS, JMIS, EJIS, ISJ, JSIS, JIT) and all outlets of the

IEEE Xplore. Our search has been limited to research articles on the assessment, detection, determination, or recognition of stress using information systems or technology in the context of humans, people, users, or individuals by using multiple search strings based on these terms. We consider only studies from 2010 and later because stress detection has gained substantial attention only since then. We found that several researchers have already exploited this data source for recognizing human psychological conditions in various ways: (1) assess stress via only a smartphone, (2) assess stress with several different devices (e.g., two smartphones or a smartphone plus an additional device such as a wearable), and (3) recognize not stress but emotions, mood, or activity (e.g., walking, running, cycling) with similar measurement techniques. The following paragraphs address these categories sequentially.

Research assessing stress using a single smartphone is rare. A literature review revealed only two applications that perform this task, both originating from the same research institution: BeWell (Lane et al. 2011) and StudentLife (Wang et al. 2014) are Android applications that assess the smartphone user’s stress level by tracking activities that affect physical, social, and mental well-being. The relevant data is collected by continuously reading several smartphone sensors, including the microphone, accelerometer, and light sensor. BeWell extends this data by integrating additional user information entered through a web portal. StudentLife pushes multiple questionnaires to the smartphone, which must be answered by the user, and extends the collected data using location-based information within the research institution’s facilities (e.g., the traveled distance inside buildings based on Wi-Fi logs). However, both applications require the user to answer multiple (an average of eight) questionnaires daily, which serve as an additional data point and are not only used for model training purposes. This makes these systems rather obtrusive. Bauer and Lukowicz (2012) identify longer stressful periods, e.g., exam weeks, from smartphone usage but do not directly assess stress.

Several applications assess stress with a smartphone plus additional devices. While both Ferreira et al. (2008) and Kocielnik et al. (2013) use external devices to measure body reactions (e.g., increased sweating, rapid heartbeats), Picard and Sano (2013) attempt to recognize stress with mobile sensors, a wrist sensor, and several daily questionnaires. Equally important, Lu et al. (2012) measure stress by analyzing the human voice and use a second phone to distinguish between speakers. Most of these applications do not enable the continuous assessment of stress, except for Kocielnik et al. (2013).

Artifacts related to stress assessment include emotion, mood, and activity detection systems. Most technical systems that aim to assess these conditions use exclusively smartphone data. The only exception is Choudhury et al. (2008), who use an external device to measure additional parameters (e.g., humidity). This data can be enriched by additional user input (Chang et al. 2011; LiKamWa et al. 2013) or gathered unobtrusively (Albu et al. 2008; Rachuri et al. 2010). In this category, Choudhury et al. (2008) and Lee et al. (2012) do not achieve a life-integrated assessment because the former uses an external device with extra information, and the latter uses a customized Twitter app instead of the original app.

In general, different research projects have shown the feasibility of basing assessments of stress or stress-related psychological factors on the human voice (Chang et al. 2011; Lee et al. 2012), sleep (Lane et al. 2011; Picard and Sano 2013; Wang et al. 2014), social interaction (Bauer and Lukowicz 2012; Wang et al. 2014), location information (Lee et al. 2012; Rachuri et al. 2010), ambient information (Lee et al. 2012), body reactions (Kocielnik et al. 2013), activity recognition (Choudhury et al. 2008), and behavioral patterns (Ferreira et al. 2008; Kocielnik et al. 2013; Lee et al. 2012; LiKamWa et al. 2013). Furthermore, the unobtrusive mobile sensing of different parameters on a single smartphone (Lee et al. 2012; Rachuri et al. 2010), which is recommended to obtain less biased data (Lee et al. 2014), is possible. Moreover, the related work shows that the continuous sensing and assessment of the user's mental state (Lee et al. 2012; Rachuri et al. 2010) is realizable, especially for emotion, mood, and activity detection (Ferreira et al. 2009; Kocielnik et al. 2013; Lee et al. 2012; LiKamWa et al. 2013). Furthermore, the unobtrusive mobile sensing of different parameters on a single smartphone (Lee et al. 2012; Rachuri et al. 2010), which is recommended to obtain less biased data (Lee et al. 2014), is possible. Moreover, related work shows that the continuous sensing and assessment of users' mental states (Lee et al. 2012; Rachuri et al. 2010) is feasible, especially for emotion, mood, and activity detection.

We found that the required level of interaction with the individual, which ranges from significant restrictions up to full integration into users' daily routine, is one of the main differences between stress assessment approaches. To the best of our knowledge, none of these systems provides a life-integrated and continuous assessment of perceived stress without interfering with the user's perceived routine constraint. In prior research (Gimpel et al. 2015), we devolved a prototype to assess perceived stress using smartphone sensing techniques. In this research, we extend the prior work-in-progress by presenting the final prototype, refining the development process and providing full data analysis of the field study.

Research Process

Our research follows the standard design science guidelines by Hevner et al. (2004) and applies the design science research methodology (DSRM) by Peffers et al. (2007), which suggests that each design science research project performs the following six activities: (1) identify the problem and motivate, (2) define objectives for solution, (3) design and develop, (4) demonstrate, (5) evaluate, (6) communicate.

Problem Identification: Modern information technology (e.g., adaptive systems) and ubiquitous sensing capabilities (e.g., in smartphones) can help to provide new solutions for the individual, societal, and economic problem stress (e.g., stress-adaptive systems).

Objectives: Design and develop a life-integrated mobile system that is capable to continuously assess a user's stress level without influencing the user's daily habits at all.

Design & Development: Stress theory lays the foundation for system design and the selection of appropriate smartphone sensors. Other systems in the context of mobile sensing, affective computing, and stress assessment provide further inspiration for the artifact. Building on this foundation, we conceptualize a mobile system that continuously gathers data about the user and its environment from stress- and strain-related smartphone sensors. The acquired data will be transformed and employed to assess the user's stress level by identifying patterns and correlations between sensed data and perceived stress.

Demonstration: The proposed system has been prototypically implemented for the Android platform. The prototype helps to demonstrate technical feasibility (operationality and effectiveness), obtain user feedback (ease of use), and collect comparative data (generality) to test the accuracy of the stress assessment analysis process (Sonnenberg and vom Brocke 2011). First releases of the prototype were provided to a selected community of alpha and beta testers before releasing a stable version.

Evaluation: To evaluate the model, we employ the prototype within a public field study to foster the results for the generality of our prototype by achieving a high external validity of the results. From that, we derive a statistical model for perceived stress solely based on data from smartphone sensors. Together, the prototype and statistical model show the design's conceptual and practical feasibility regarding operationality and effectiveness as well as the practical utility of life-integrated and continuous mobile stress assessment, considering the ease of use for the prototype's users.

Communication: Finally, we communicate our research in line with Gregor and Hevner (2013). A preliminary version of this research has already been presented at a conference (Gimpel et al. 2015), while it was still in progress but did not yet include data analysis and evaluation. Valuable feedback from the research community was integrated into the design and presentation of the results.

Prototype

Requirements

Based on the design objective and related work, we identify three relevant requirements: (1) life integration, (2) assessment continuity, and (3) abidance to non-functional requirements for medical mobile systems.

Life-Integration: To minimize intruding effects and reduce bias, the system needs to be fully integrated into the user's life, i.e., it must not be perceived as an additional stressor or interfere with the user's perceived routine constraints. Studies have also highlighted the stress-inducing aspect of questionnaires (Intille et al. 2003; Scollon et al. 2003). Moreover, periodically appearing questionnaires are likely to stress people and can consequently bias the assessment. Thus, users must not be explicitly and regularly surveyed on their current stress level (except for model alignments, which should be used rarely).

Continuity: Stress varies over time, potentially in short cycles. As appraisal steps permanently (re-)evaluate stressors to determine stress, it is crucial that the system must be capable of grasping changes in the person's current situation. Thus, the system must deliver a plausible assessment of the user's current stress level whenever requested to allow for effective intervention and adaptation. In the future, we aim to perform computations directly on the smartphone and limit the use of internet services.

Medical mobile non-functional requirements: The European Commission (2016) recently published a Code of Conduct on privacy for mHealth apps, which addresses the problem of the often discussed privacy concerns on mobile apps (Gimpel et al. 2018), particularly in the health context. This code further provides guidance to app developers and publishers regarding the display of certain application practices information. Hence, in order to provide a high level of quality, the system must adhere to the medical mobile non-functional requirements presented by Meulendijk et al. (2014): accessibility, certifiability, portability, privacy, safety, security, stability, trustability, and usability.

Prototypical Instantiation

The assessment of stress using life-integrated smartphone sensing requires a user-centric development process. In several development and deploy cycles, we developed and continually evaluated an Android prototype. Six alpha testers (the authors and three testers outside the research team) provided feedback that helped to refine the prototype and create a more mature artifact prior to releasing the app to a larger beta testing group. This group consisted of 8 participants with different smartphones and different operating system versions. Feedback from beta testing helped finalize the application as a ready, multilingual app (German and English) that could be used within a global field study without major constraints on the device or operating system version. The lean user interface (Figure 14) has been designed together with usability professionals. The prototype embeds into a general architecture consisting of four major components: 1) The smartphone user and their surroundings, 2) the smartphone's hardware sensors as transitions between the social and the technical part of the system, 3) the prototype capturing sensor data and periodically uploading it into a cloud storage, and 4) model building of a stress assessment model.

The application is designed to read 38 hardware and software smartphone sensors in order to empirically identify sensors that might be valuable for stress assessment. These sensors are the outcome of a conceptual evaluation of available smartphone sensors and the unobtrusive smartphone-based measurability of stressors and strains from the stress model (Figure 5 in section 2.3). Here, we focus on sensors that can provide us with information on either the user or their environment. For this purpose, we rely on information from hardware sensors to determine parameters of the environment (e.g., temperature, noise, location) and software sensors (i.e., using sensor fusion to process multiple basic information to more complex information) to collect behavioral or environmental data (e.g., typing behavior, sentiment analysis of incoming/outgoing calls, calendar information). The individual correlation of a sensor with perceived stress and its ability to contribute to stress detection in a portfolio of sensors is a question for subsequent empirical evaluation. We do not hypothesize and evaluate a causal relationship between sensors and stressors or strains from the stress model but aim at stress prediction.

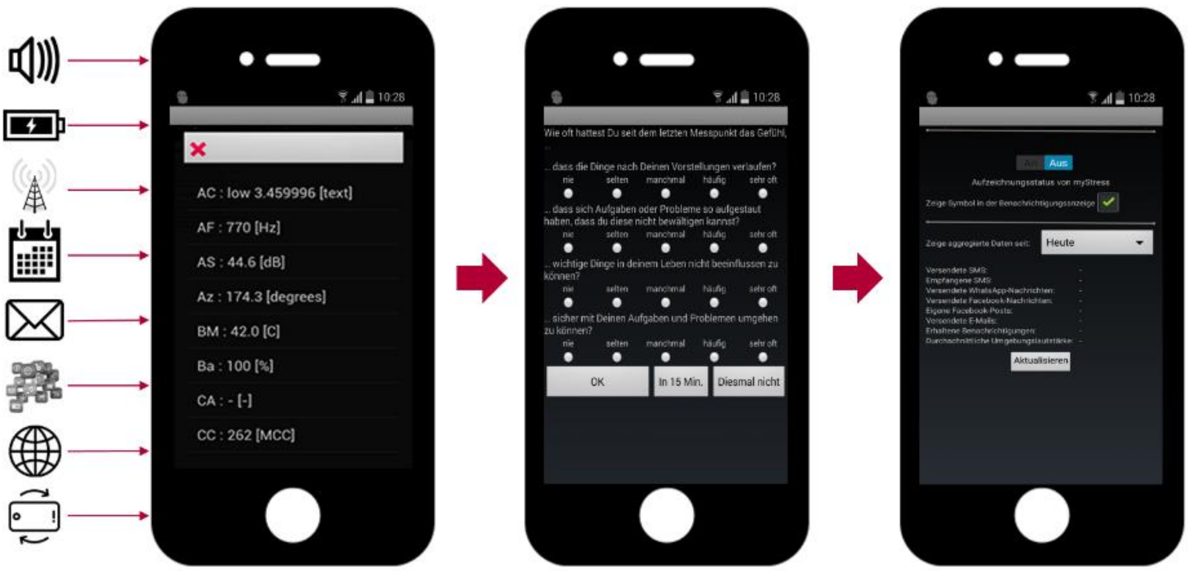


Figure 14: Screenshots of the Application

The implemented sensors can be divided into two categories. Sensors of the first category probe at a defined time interval, e.g., the ambient temperature, audio frequency, and illumination sensors. A high probing frequency of only a few seconds in the alpha version led to very high battery consumption and low battery life of the testers' smartphones. Feedback included that a minimum battery life of 24 hours, given normal smartphone use, would be desirable. As a trade-off between granularity of measurement and resource efficiency, we set the probing interval to 5 minutes in the final version of the prototype. Sensors of the second category respond to specific events, e.g., incoming or outgoing text messages, the pressing of the power button, or notifications. Event sensors can count the number of occurrences, identify state changes, or store additional information like the sentiment of an outgoing text message or the duration of a phone call. In the alpha release, extended data such as the full message text or the caller ID was stored but reduced due to severe privacy concerns. Table 19 features the full list of sensors that reference at least one stressor or strain from the stress model. The resulting list features many physical and psychological stressors as well as behavioral strains. References to physical and cognitive strains (e.g., reduced typing accuracy) are present but rarer. However, mobile sensors can cover not all aspects of the stress model, as a holistic stress assessment requires contextual data (e.g., information on the workplace), explicit user input (e.g., on emotions), or physiological measurements (e.g., sweating).

In order to assess the relationship between sensors and perceived stress, the prototype asks the user three times a day (at morning, midday, and evening) to answer a short stress questionnaire on their smartphone. While this questionnaire is not unobtrusive, it is only included for researching how to assess stress unobtrusively – we aim to make it redundant and spare it within the final system. The questionnaire consists of the 4-item Perceived Stress Scale (PSS-4) proposed by Cohen et al. (1983), which is one of the most frequently used scales to assess perceived stress. It uses four items on a 5-point Likert scale ranging from 0 to 4 to measure the individual's stress perception based on stress-inducing aspects of life (unpredictability, uncontrollability, and overload). The questions are phrased in natural language and, hence, independent of content and population. The final score calculates as the sum across all four items, whereby two items are reversed.

The PSS was shown to be a valid measure for linguistically quantifying stress sensed by a human being and is frequently used in research (Haushofer and Fehr 2014; Heidt et al. 2014; Hobfoll 1989). Unless the fact that PSS cannot be used as a diagnostic instrument, it is suitable to perform comparisons (Cohen 2015). Although the PSS-4 has lower internal reliability than the longer 14-item version (PSS-14), it provides much more usability for measuring perceived stress over spatial distance (Cohen et al. 1983). In this trade-off between internal reliability and usability, we chose usability to be an important aspect of the present study. We try to eliminate the questionnaire as a confounding variable to reduce bias. The original questionnaire design by Cohen et al. (1983) enquires how often participants felt a certain way in a specific period (originally one month). Although the classic version of PSS-4 uses one month, it remains valid on significantly smaller periods (Cohen 2015). Thus, we changed the original PSS-4 wording "In the last month, how often have you felt […]" to "Since the last survey […]" for all four items: 1) "[…] that you were unable to control the important things in your life?", 2) "[…] confident about your ability to handle your personal problems?", 3) "[…] that things were going your way?", and 4) "[…] difficulties were piling up so high that you could not overcome them?". The scores of items 2 and 3 are inverted for summation.

To maintain general data privacy and to adhere to the Code of Conduct (European Commission 2016), the user has to manually activate data collection after installation and can pause it at any time. The prototype uploads the data twice a day to a cloud storage. This interval reflects a trade-off between data timeliness and resource consumption. In order to spare the user's limited data connection, the upload only occurs with an existing Wi-Fi connection. On the resulting data set, we explored associations of sensors and perceived stress using regression and classification models.

Evaluation

In this subsection, we evaluate the generality, ease of use, effectiveness, and operationality (Sonnenberg and vom Brocke 2011) of the proposed system for life-integrated assessment of stress based on the Framework for Evaluation in Design Science Research (Venable et al. 2016) with consideration of the requirements. Following Venable et al. (2012) and Sonnenberg and vom Brocke (2011), this evaluation serves three purposes: (1) Evaluate the prototype formatively while under development, (2) evaluate the effectiveness and ease of use of the prototype for the mobile sensing of stress-related factors, and (3) evaluate the operationality and generality of model building for stress assessment upon the unobtrusively gathered data.

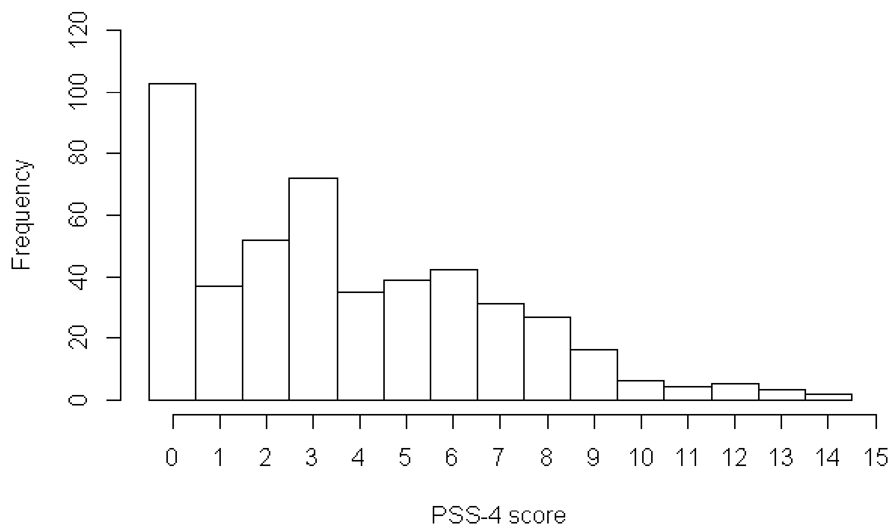
The presented artifact – a prototypical mobile system for life-integrated assessment of an individual's perceived stress – can be considered a socio-technological process artifact (Venable et al. 2012) demonstrating the assessment of human stress based on smartphone data. We evaluate the system using design science and prototyping evaluation methods (*Proceedings of the 7th International Conference on Design Science Research in Information Systems and Technology*, 2012; Hevner et al. 2004) and perform five consecutive evaluation episodes (Venable et al. 2016): 1) Literature-backed design and ex-ante validation of sensors' relevance and theoretical utility, 2) agile development of the prototype including alpha and beta testing to ensure ease of use, 3) examination of operationality and generality of life-integrated sensing in the field study, 4) data analysis and model building of a general stress assessment model including performance tests for determining its effectiveness, and 5) operationality and performance of model personalization. A further episode that comprises ex-post evaluation activities similar to Eval4 (Sonnenberg and vom Brocke 2011) should test the system's applicability to advanced application scenarios such as stress-sensitive adaptive enterprise systems. This is yet up to future research.

<u>Episode 1 – Literature-backed Design:</u> In the Foundation subsection, we elaborated a schematic concept for mobile stress assessment supported by literature on stress and mobile sensing as a first review of formative knowledge, which the application and its sensors are based on.

<u>Episode 2 – Agile Development:</u> The Prototype subsection describes insights into critical success factors we gained during agile prototyping. In the first versions of the prototype, alpha

and beta testers expressed severe security and privacy concerns; these were addressed by transparently communicating what the system does and does not measure. The prototype also suffered from inefficient resource use; this was corrected by eliminating power-consuming defects and reducing sensor-probing frequency.

Episode 3 – Public Field Study: We apply the prototype within a field study to evaluate its acceptance among users and determine the general operationality of life-integrated mobile stress assessment. To reach a broad and diverse audience, we published the prototype in the Google Play Store and recruited participants in social media, particularly via Facebook, Twitter, and Quantified Self forums. The app was installed on 222 devices (96 from Germany, 50 from the US, 19 from India, and 13 from Brazil) and 137 different smartphone models with Android versions ranging from 2.3.3 to 5.0.1. However, during the four months of data collection, only 40 users provided an informative dataset of sensor data in combination with at least one answered stress questionnaire in total. Several factors might have contributed to the discrepancy between installations and data provision: a non-existing Wi-Fi connection could have impeded data upload, data privacy concerns could have prevented the user from activating data collection, or users could have installed the application out of curiosity without the actual intention to support our research. In addition, there was no incentive for participation. Instead, we relied on the users' motivation to support research and to potentially benefit from a more mature system in the future. Anecdotal evidence suggests that the strongest reason for not participating is the lack of perceived usefulness, as the prototype only gathers data but does not yet provide feedback or intervention recommendations. We plan to add this in future versions.



Note: The PSS-4 scale ranges from 0 (no stress) to 16 (high stress)

Figure 15: Distribution of Perceived Stress in the Field Study (n = 474)

The 40 participants, who uploaded at least one questionnaire, answered the questionnaire 474 times in total (an average of 11.5 questionnaire reports per user). The following data analysis is restricted to these 40 users, as the ability to build a statistical model for stress assessment hinges on the availability of questionnaire data, even if this data is not part of the final system. The overall distribution of PSS-4 scores in our user base (Figure 15) aligns with representative surveys on the distribution of stress (Cohen and Williamson 1988; Statista 2010; Warttig et al. 2013). Although this shows a clear trend towards low levels of perceived stress, we observed differences in stress intensity over time and between users.

Since we did not incentivize participation in the field study, the general interest and enduring commitment of participants during the field study suggests that users are open to the idea of life-integrated stress sensing. The successful deployment and data collection of the prototype in the field study substantiate the operationality of life-integrated sensing. A caveat is the high rate of non-users, presumably because the prototype did not provide any benefit or valuable feedback to users.

Episode 4 – Data Analysis and Model Building: We evaluate the prototype's effectiveness by using the data gathered within the field study to create a universal, that is, person-independent, model for the assessment of perceived stress. For analysis, we link each stress level observation with recent sensor data and test regression and classification performance. Pre-processing presumes that the analysis of linear relationships might not be sufficient and, thus, extends the number of features by performing various transformations on the raw data. In this course, we logarithmize the data, independently apply a median split, and include the untransformed data. The same transformations are performed on a copy of the raw data, in which outliers, i.e., sensor values that are not within the interval of 1.5 interquartile ranges from the lower and upper quartile of each sensor, are censored. As outliers might be a valuable indicator for exceptionalities causing stress, we do not fully remove them. For feature creation, we aggregate all data between two stress level observations, calculate the minimum, maximum, range, median and mean for numerical data, and count occurrences in absolute numbers and normalized to one hour for categorical and event data. Time features for the daytime (morning, midday, evening) complete the feature list. In case of missing values, we assume normality and replace them with the variable's median.

This pre-processed data provides the foundation for training a regression model that predicts stress levels on the PSS-4 scale (ranging from 0 to 16). Standard linear regressions (ordinary least squares, panel, or stepwise regressions) are not applicable because the data presents the problem of high dimensionality with a substantially larger number of variables than observations) and, thus, harbor the danger of overfitting. Instead, we use three linear methods suitable for high-dimensional regression problems (Hastie et al. 2005), elastic net regression and its two special forms ridge and lasso regression. As model sparsity is an important issue in mobile processing, we evaluate model performance in predicting the level of perceived stress based on the adjusted R^2 in cross-validation (Alpaydin 2004). Although the elastic net produces less prediction error, we find that the best model selected according to adjusted R^2 is based on lasso regression fitting. It explains 41 % of the variance in users' perceived stress, uses 94 variables from 21 of the 38 sensors in total (Table 19), and achieves an adjusted R^2 of 0.26 with a root mean squared error (RMSE) of 2.69 and a mean absolute error (MAE) of 2.12 on the 0 to 16 scale.

To check the robustness of the results, we test if users with a low number of observations (e.g., those supplying questionnaire data only once) could falsify the regression model. Thus, we additionally analyze the subsets of users with at least ten or at least twenty stress level observations. The best model for users with ten or more observations achieves an in-sample cross-validation RMSE of 2.46 and generalizes with an RMSE of 2.69 when applied to the dataset of all users, including those with fewer observations. The result further improves for twenty or more observations with an in-sample RMSE of 2.11; however, an evaluation against all users returns an RMSE of 3.03. Not surprisingly, fit statistics improve when reducing the dataset, as the model can better approximate a smaller number of users. Another interesting discovery is that the RMSE from validating against all users is minimally affected, irrespective of whether training is performed with data from all users or data from users with at least ten observations. This suggests that no overfitting problem exists with the best regression model.

As a further robustness check, we additionally train a classification model, which aims to distinguish the two categories 'no stress', which denotes PSS-4 scores from 0 to 3, and 'stress', which represents the scores 4 and above. We set the boundary at 4 because this score implies that, on average, each item of the PSS-4 scale has been answered with a value of 1, which we assume to be a reasonable and legitimate minimum condition for the 'stress' category. While all three binary classification models we trained – a boosted decision tree (BDT), a decision forest (DecFo), and a support vector machine (SVM) – achieve good overall performance in a ten-fold cross-validation setting, the BDT performs best. It predicts the correct category with an accuracy of 81 % (DecFo 80 %, SVM 75 %), and achieves a precision of 78 % (DecFo 77 %, SVM 72 %) and a recall of 80 % (DecFo 79 %, SVM 72 %) for predicting the presence of stress with an area under the ROC curve (AUC) value of 0.86 (DecFo 0.85, SVM 0.82).

Sensor	Description and unit of measurement	Model
Connectivity		
Cell Identifier	Identifier of the current cellular network [nominal]	no
Location Area Code	Location area code of the current cellular network [nominal]	no
Network Code	Network code of the current cellular network [nominal]	no
Data Connection Status	Is the device currently connected to cellular data [binary]	yes
Roaming Status	Is device currently roaming [binary]	no
Wi-Fi Connection Status	Is device currently connected to a wireless network [binary]	yes
Battery		
Battery Charging Status	Is device currently charging [binary]	no
Battery Level	Current battery level [%]	yes
Battery Temperature	Current temperature of the battery [°C]	yes
Mobility & Activity		
Orientation	The device’s current azimuth, pitch, and roll [3x degrees]	yes
Activity	Variance of device’s orientation and its interpretation [none/low/high]	yes
Step Counter	Changes on device’s pedometer within the poll interval [steps]	no
Communication		
Calendar Events	Number of calendar events within 24 hours [count]	no
Call Log	Number [count], duration [min] and type [in/out] of phone calls	yes
Incoming Text*	App-specific notification about incoming messages [event]	yes
Outgoing Text*	App-specific notification about outgoing messages [event]	yes
Text Length*	Length of outgoing messages [characters]	no
Text Sentiment*	Sentiment of outgoing messages [positive/neutral/negative]	no
Typing Speed*	Typing speed of outgoing messages [characters per min]	yes
Typing Accuracy	Number of deleted characters [count]	no
Smartphone Usage		
RAM Available	Currently available memory (RAM) [KB]	no
Running Apps	Number of currently running apps (multiple possible) [count]	yes
Visible Apps	Number of currently visible apps (multiple possible) [count]	yes
Screen Switching	Indicates that user switched screen over [event]	no

Sensor	Description and unit of measurement	Model
Environment		
Ambient Light	Brightness of current ambient light [Lux]	yes
Ambient Audio	Amplitude [dB] and frequency [Hertz] of current ambient sound	yes
Ambient Temperature+	Temperature of the smartphone’s environment [°C]	no
Ambient Humidity+	Humidity of the smartphone’s environment [%]	no
Ambient Pressure+	Atmospheric pressure in the smartphone’s environment [bar]	yes
Proximity+	Distance of the smartphone to the next object [meter]	no
Location	Latitude [degree] and longitude [degree] of the current location	no
Location Changes	Frequency of minor location changes [count]	yes
Weather: Temperature	Temperature at the current location [°C and °F]	yes
Weather: Humidity	Humidity at the current location [%]	no
Weather: Wind	Wind speed at the current location [miles per h]	yes
Voice		
Voice Energy	Energy of voice signal using L1-, L2- and Linf-norms [ordinal]	yes
Voice Spectral Density	Power spectral density of 50, 250, 500 and 1000Hz [ordinal]	yes
Voice Frequency	Frequency spectrum using 12 MFC coefficients [ordinal]	yes

Notes: ‘*’ currently supports SMS, WhatsApp, Facebook Messenger, and mail apps
‘+’ only available on some devices.

Table 19: List of Sensors in the Prototype and Their Relevance in the Best Regression Model

Discussion and Implications

We designed and developed a system for life-integrated stress assessment with consideration of both psychological literature on stress and comparable scientific efforts on the sensing of psychological phenomena. The prototype fulfills all design requirements: Data was gathered continuously in a life-integrated way with adherence to important non-functional requirements. The PSS-4 surveys were only used for validation; they are not part of the design itself. The achievement of reasonable performance in assessing perceived stress levels shows the general feasibility of life-integrated stress assessment via smartphone. The best regression model, which was selected by the criterion of minimum adjusted R^2, predicts PSS-4 scores on a scale ranging from 0 to 16 with an average accuracy (MAE) of +/-2. There are no guidelines or benchmarks specifying acceptable performance for this type of system in an uncontrolled environment and we do not claim that our method of statistical analysis is optimal. However, we do claim that explaining 41 % of the variance in perceived stress is substantial for a system, which does not at all require user cooperation in daily use.

During agile prototyping, we gained various important insights into critical success factors of life-integrated stress assessment systems. In their combination, these learnings help with details on the design of life-integrated stress assessment and might help researchers and practitioners likewise to build better systems. Most importantly, the accessibility of stress assessment is vital for its use and acceptance. Obtrusiveness, that is, the necessity of attention or interaction with the user, puts up high barriers for broad application. Our research shows that life-integrated stress assessment is feasible and a valuable approach to stress assessment. But it also shows that excessive resource consumption, in terms of data storage or upload, battery consumption, or processing power, might already be partially obtrusive as it brings the system's existence into the user's attention. Another very important facet is, for example, to consider the protection of the user's privacy. For some people, the stress level itself is highly sensitive information. This holds especially true when the information is shared with others, e.g., with the employee's supervisor in organizational stress management applications. Privacy is even more important with the full set of sensor data that allows for the creation of movement, usage, and behavior profiles. Consequently, applications should establish appropriate privacy protection mechanisms that prevent external access to sensitive information on a need-to-know basis (Sutanto et al. 2013). One potential measure could be to fully renounce an internet-based data upload and perform computations fully on the user's device. As a third learning, user feedback suggests that they are significantly more tolerant towards limited privacy and resource-saving if the system provides a clear benefit to the user.

The manifold application scenarios target several stakeholder groups for the concept of life-integrated stress assessment range from pure information provision to detailed feedback or the automation of stress-reducing routines. The most obvious scenario is the immediate use to support the individual user. Stress assessment can be directly used to support the user's stress management by providing feedback on the current stress level. Mobile apps for personalized and sentiment-dependent recommendations can use the stress level to recognize the individual's need for relaxation. The recently suggested design of stress-sensitive adaptive enterprise systems (Adam et al. 2017) can be operationalized building on the presented life-integrated, continuous stress assessment and help business and users likewise. Stress-related lack of concentration in hazardous work scenarios such as the interaction with robots or machines can be tackled with countermeasures for the benefit of human safety. Similar purposes are imaginable for the support of business-critical decisions: a stock exchange app, for example, can take the increased risk propensity of the stressed individual into account and warn them of risky trades in advance. Furthermore, personalized stress-aware design and adaptation of user interfaces can help improve customer experience. These examples illustrate the broad range of application scenarios that emerge from the possibility to unobtrusively evaluate the stress level of individuals whenever and wherever required.

Conclusion

In this section, we presented a system targeting the life-integrated and continuous smartphone-based assessment of perceived stress. We followed the design science research methodology of Peffers et al. (2007) and elaborated the system in several steps. Based on problem relevance, theoretical background, and design requirements, an exemplary implementation for the Android platform has been developed. This prototype helped to demonstrate the general operationality of life-integrated mobile sensing and its applicability for the assessment of perceived stress. A binary classifier demonstrates its value for determining stressed and non-stressed mental states. The universal stress assessment regression model elaborated in this work links data from smartphone sensors to their application for stress valuation and confirms the feasibility of life-integrated and continuous stress assessment. This model is based on data gathered within a public field study, in which 40 users provided data by using the prototype. Therefore, the presented method enables the development of systems that apply a life-integrated and continuous assessment of perceived stress as input for adaptation mechanisms that provide targeted technological or manual stress management interventions. Furthermore, the method can be used as an indicator for the user's current affective state to provide relevant information to user-adaptive systems enabling a more intuitive interaction Morana et al. (2017).

Some aspects of the present study call for subsequent research to further test and extend our results. First, stress is a multi-faceted phenomenon. We targeted perceived stress, which is not necessarily identical to actual stress (Riedl 2013). Thus, going beyond perception towards physiological measurements will be a valuable addition to the present research. Second, our system relies on the regular usage of one primary smartphone. The exact boundaries of the scope are not yet clear. Future field tests should measure the intensity of smartphone usage and recruit participants with diverse intensities to explore how intense smartphone interaction must be for reliable stress assessment. Third, it is by no means clear that a technological solution for perceived stress assessment is the most appropriate solution because smartphones themselves are potential stressors (Lee et al. 2014). Nevertheless, we contend that it is worth exploring and evaluating how smartphone-based sensing can foster the development of innovative technologies that appropriately interact with the stressed or chilled individual. Fourth, the results of the study should be confirmed on a larger dataset that features more participants and a longer evaluation period. Fifth, an evaluation involving the actual use of stress assessment in a realistic application context should be conducted. Sixth, refined statistical models or aggregation may improve model performance. For example, future research could investigate what amount of historical sensor data is best to predict stress. Moreover, the value of personalized models is worth exploring. For new users, stress assessment could initially be based on a pre-trained general model as presented in this section; the model could then be improved over time through personalization, similar to the approach Rachuri et al. (2010) use for personalized emotion detection. Finally, future work should link stress assessment with stress management interventions. A first step might be providing feedback to users. From a wider perspective, unobtrusive and continuous assessment of perceived stress can be the foundation for stress-adaptive information and enterprise systems, as suggested by Picard and Liu (2007) and Adams et al. (2017; 2014).

5.2. Composing a Design Theory for Mobile Stress Assessment

The prototypical instantiation of a life-integrated mobile stress assessment system presented in the previous section demonstrated that the assessment of stress based on data from mobile sensors is feasible without interfering with the user's daily routines. Yet, different application purposes of mobile stress assessment (MSA) may require differently designed solutions. Therefore, this section aims to grasp the diversity of current mobile stress assessment approaches and applies this extended lens to explore how applicable and effective MSA systems for different application purposes can be designed.

More and more employees report increasing workloads and blurring boundaries between work and private life, contributing to an overall increase in stress. In part, this is driven by the increasing use of ICT, which leads to technostress (e.g., techno-invasion and techno-overload; Tarafdar et al. 2007). Beyond the effects of digitalization, there are many other stressors (e.g., timing conflicts, financial problems, or bad health of a loved one; Kanner et al. 1981). The resources available to cope with these stressors do not rise to the same extent. This disbalance carries the risk to potentially deteriorate personal well-being (Riedl 2013) and cause severe illnesses such as burnout or depression (Hammen 2005). Consequently, the demand for stress management support is rising. Despite drawbacks like creating technostress, ICT may also deliver a solution and assist individuals in managing stress (vom Brocke et al. 2013; vom Brocke et al. 2020a). Various scholars recently called for intensified efforts to develop smart assistants that are sensitive to and promote individuals’ health (Stephanidis et al. 2019; vom Brocke et al. 2020a) or provide assistance with stress management (Adam et al. 2017).

An essential prerequisite for practical stress management assistance is the assessment of individuals’ stress. Typical stress assessment methods such as psychological questionnaires (Cohen et al. 1983) or hardware-based physiological measurements (Riedl 2012, 2013) have a decisive disadvantage because their automation capacity and mobility are limited. Modern mobile devices’ sensing capabilities facilitate a data-driven approach that uses data analytics methods to relate acquired data on the user and their environment with stress. This MSA can target multiple application purposes, for example, assisting individuals in coping with stress (Adam et al. 2017) or increasing human safety by preventing dangerous situations (Sandulescu and Dobrescu 2015). So far, MSA research has focused on demonstrating its feasibility for various application purposes (Gimpel et al. 2015, 2019b; Lane et al. 2011; Lu et al. 2012; Wang et al. 2014) but has not yet integrated reusable design knowledge. Although existing instantiations employ similar designs and some studies report implicit design-related learnings, generalizable guidelines and theoretical knowledge on designing MSA systems are yet missing. We argue that such knowledge is vital to promote the further application of and theory development on MSA and facilitates the development of high-quality MSA systems and, prospectively, IS assisting in stress management. Hence, we strive to close this gap and pose the design objective to *compose a design theory for mobile stress assessment systems*.

We follow standard design science research (DSR) methodology (Hevner et al. 2004; Peffers et al. 2007) to develop a design theory (Gregor 2006; Gregor and Hevner 2013; Gregor and Jones 2007) for MSA systems with a special focus on reviewing MSA literature. For this purpose, we analyze the existing literature on the domain and extract and consolidate design knowledge from the learnings of 136 MSA studies. Further, we generate new design knowledge by implementing five MSA system prototypes. Based on this design knowledge, we compose the design theory from several interrelated elements: a set of *design requirements* specifies MSA systems’ purpose, a *design blueprint* depicts MSA systems’ typical architecture, *design principles* emphasize important considerations when designing an MSA system, and *design features* detail the implementation of the blueprint and principles. Further, we show *trade-offs* between design requirements and design features that may be necessary when implementing a specific MSA system. Altogether, these elements contribute to DSR literature by providing an example of a theoretically grounded and empirically enhanced design theory that can inspire other scholars to strive for consolidated design knowledge and facilitate effective IS development.

This section is structured as follows. The first subsection presents theoretical foundations for mobile stress assessment and derives six design requirements. The second subsection describes our research process. The third subsection presents elementary MSA design knowledge emerging from the literature analysis. Building on this, the fourth subsection distinguishes five archetypes of MSA systems prevailing in the current literature. The fifth subsection analyzes trade-offs arising when implementing MSA systems according to our design theory. The sixth subsection discusses the results and presents the composition of the design theory. Finally, the seventh subsection concludes with a critical reflection of our research.

Theoretical Foundation

Our research builds on the theoretical concept of human stress (section 2.3) and is informed by a multitude of literature on mobile stress assessment. This subsection first portrays the diversity of extant MSA research and then elaborates the underlying design requirements of MSA.

Mobile Stress Assessment

Due to the subconscious nature of the human stress reaction, individuals often do not understand why stress is building up (Müller et al. 2011). Feedback that makes transparent to an individual why they experience stress could help them activate appropriate coping responses (Adam et al. 2017). Therefore, IS literature recently called for stress management and prevention systems (Adam et al. 2017; Friemel et al. 2017; vom Brocke et al. 2020a). As a prerequisite for advanced stress management, a broad research stream targets assessing individuals' stress using mobile hardware. In this dissertation, we refer to MSA systems as a class of mobile IS that use sensor data on the user (e.g., physiological and behavioral data) and their environment (e.g., environmental conditions) to determine the user's stress state for a specific application purpose (e.g., enabling individual stress management, mitigating the dangers of stress at the workplace). MSA needs to be reliable and "minimize retrospective biases while gathering ecologically valid data, including self-reports, physiological or biological data, and observed behavior, for example, from daily life experiences" (Trull and Ebner-Priemer 2013, p. 1).

Five literature reviews have recently structured literature on and adjacent to MSA: Þórarinsdóttir et al. (2017) published a comprehensive review of existing literature on smartphone-based stress assessment. Aigrain (2016) analyzed different strategies for detecting stress in various settings. Greene et al. (2016) published a survey on affective computing for stress detection. The review by ur Rehman et al. (2015) examined the capability of mining personal data collected via smartphones and wearable devices. Glenn and Monteith (2014) researched medical and commercial projects on pervasive healthcare enabling remote disease monitoring, including stress. Building on these reviews, we found that scholars exploit data from mobile devices to recognize human psychological conditions in various ways: (1) assess stress via only a smartphone, (2) assess stress with several different devices (e.g., two smartphones or a smartphone plus an additional device such as a wearable), and (3) recognize not stress but emotions, mood, or activity (e.g., walking, running, cycling) with similar measurement techniques.

Research assessing stress using a single smartphone is rare. BeWell (Lane et al. 2011) and StudentLife (Wang et al. 2014) are Android applications that assess smartphone users' stress levels by tracking activities that affect physical, social, and mental well-being. The relevant data is collected by continuously reading multiple smartphone sensors, including the microphone, accelerometer, and light sensors. BeWell extends this data by integrating additional user information entered through a web portal. StudentLife pushes multiple questionnaires to the smartphone that the user must answer and extends the collected data using location-based information within the research institution's facilities (e.g., the traveled distance inside buildings derived from Wi-Fi logs). Bauer and Lukowicz (2012) do not directly assess stress but identify longer stressful periods, for example, exam weeks, from smartphone usage.

Several applications assess stress with a smartphone plus one or more additional devices. Both Ferreira et al. (2008) and Kocielnik et al. (2013) use external devices to measure body reactions (e.g., increased sweating, rapid heartbeats), Picard and Sano (2013) attempt to recognize stress with mobile sensors, a wrist sensor, and several daily questionnaires. Lu et al. (2012) measure stress by analyzing the human voice and use a second phone to distinguish between speakers.

Artifacts related to but not directly performing stress assessment include emotion, mood, and activity detection systems. Most technical systems aiming to assess these conditions use smartphone data exclusively. An exception is Choudhury et al. (2008), who use an external device to measure additional parameters (e.g., humidity). This data can be enriched with additional user input (Chang et al. 2011; LiKamWa et al. 2013) or gathered unobtrusively (Rachuri et al. 2010).

Most of the systems presented in the previous paragraphs target the assessment of everyday stress or stress for certain groups of people (e.g., students in their exams). However, some MSA system instantiations serve other use cases. Sandulescu and Dobrescu (2015) describe the development and use of a wearable shirt to detect stress experienced by firefighters in action. This system aims to proactively warn mission supervisors about excessive stress levels of one or more persons in their action force to prevent potential dangers for their people and their mission. Other studies suggest using wearable gloves to measure a driver's stress indicated by steering wheel movements (Lee and Chung 2017). Similarly, Rodrigues et al. (2015) aimed to identify location-based stressors for public bus drivers systematically. Although these application purposes of MSA systems are somewhat exotic, they show the broad bandwidth and high potential of MSA. Thus, our design theory aims to hold for all MSA systems independently of the purpose they fulfill.

Design Requirements

A closer investigation of the exemplary MSA systems described in the previous subsection reveals that they all share the same high-level design requirements (DRs). These design requirements describe essential properties that characterize MSA systems and specify their purpose and scope. Three design requirements refer to MSA systems' functional system behavior (DR1-3); another three design requirements refer to the system's quality (DR4-6).

DR1 – Gather valid data on the user and their environment: The validity of the input data is an essential prerequisite for MSA. Due to the different causes and manifestations of stress, MSA requires a comprehensive picture of users' stress experience. Therefore, MSA systems collect data on the user (e.g., physiological data, behavioral data, or data from introspection; Ayzenberg et al. 2012; Wang et al. 2014; Gimpel et al. 2015) and their environment (e.g., noise, temperature, or air pressure; Mayya et al. 2015) in a rigorous way.

DR2 – Determine stress suitably. Given valid data, MSA systems need to employ appropriate methods to ensure the suitability of stress assessment. However, there is no one-fits-all solution. One must design the stress calculation explicitly for the respective use case, for example, prioritizing emergency calls according to the caller's detected stress level (Lefter et al. 2011). The respective design may vary regarding the stress level's granularity or model personalization (Garcia-Ceja et al. 2016). Thus, this requirement affects various aspects of an MSA system.

DR3 – Report the results to a defined recipient understandably and transparently. Given reliable stress determination, MSA systems finally report or present their results. The specific form and recipient of the reporting depends on the MSA system's application purpose. To report a binary classification result (i.e., stress or no stress) such as used by Bogomolov et al. (2014), other means may be suitable in comparison to the reporting of interval-scaled stress scores such as Garcia-Ceja et al. (2016).

DR4 – Keep the system's technical resource consumption at an appropriate level. MSA systems typically should handle technical resources (e.g., amount of data, storage capacity, computing time, or electric power) to cater to high mobility. Again, the specific demands going along with this requirement depend on the application. When the MSA system performs all computations directly on a mobile device (e.g., Bauer and Lukowicz 2012; Bogomolov et al. 2014), computing power, storage, and battery capacity are limited. When a system adopts a client-server architecture (e.g., Lane et al. 2011; Ayzenberg et al. 2012) to overcome this issue, data throughput between client and server might be limited.

DR5 – Choose an appropriate level for algorithm accuracy: Many MSA systems use machine learning techniques to detect stress from gathered data (e.g., Calibo et al. 2013; Hovsepian et al. 2015; Mayya et al. 2015). Depending on the data quality, the specific algorithm, or the degree of model personalization, achievable accuracies may vary. For example, an MSA system used for medical stress diagnosis must provide more accurate results than a system assisting users in improving their everyday well-being.

DR6 – Provide a high level of user acceptance: MSA systems must meet user demands such as privacy and unobtrusiveness. Some MSA systems capture sensitive data such as physiological data (Mayya et al. 2015; Rodrigues et al. 2015), behavioral data, or personality traits (Bogomolov et al. 2014). Hence, a high level of privacy is essential for user acceptance. Meulendijk et al. (2014) list privacy as a separate design dimension in their list of non-functional requirements for mobile apps in the context of health. In contrast to the previously presented design requirements, user acceptance is not fundamentally dependent on the application purpose but should always be kept on a high level.

Methodology

Our research addresses the design objective of composing a design theory for MSA systems. It employs the DSR methodology by Peffers et al. (2007) with integrated evaluation activities following Venable et al. (2016) and Sonnenberg and vom Brocke (2011). We employ the Human Risk & Effectiveness evaluation strategy from Venable et al. (2016) as our design theory needs to demonstrate its effectiveness for producing MSA systems that assess the user's stress in realistic scenarios. Figure 16 presents the design and evaluation process.

Step 1: Literature Review. We review stress literature to inform our research with relevant knowledge of the problem space (vom Brocke et al. 2020b) and exemplary MSA literature to evaluate our research's importance and novelty from an ex-ante perspective (Sonnenberg and vom Brocke 2012; Venable et al. 2016). This step produces relevant design requirements for MSA systems determined from the literature.

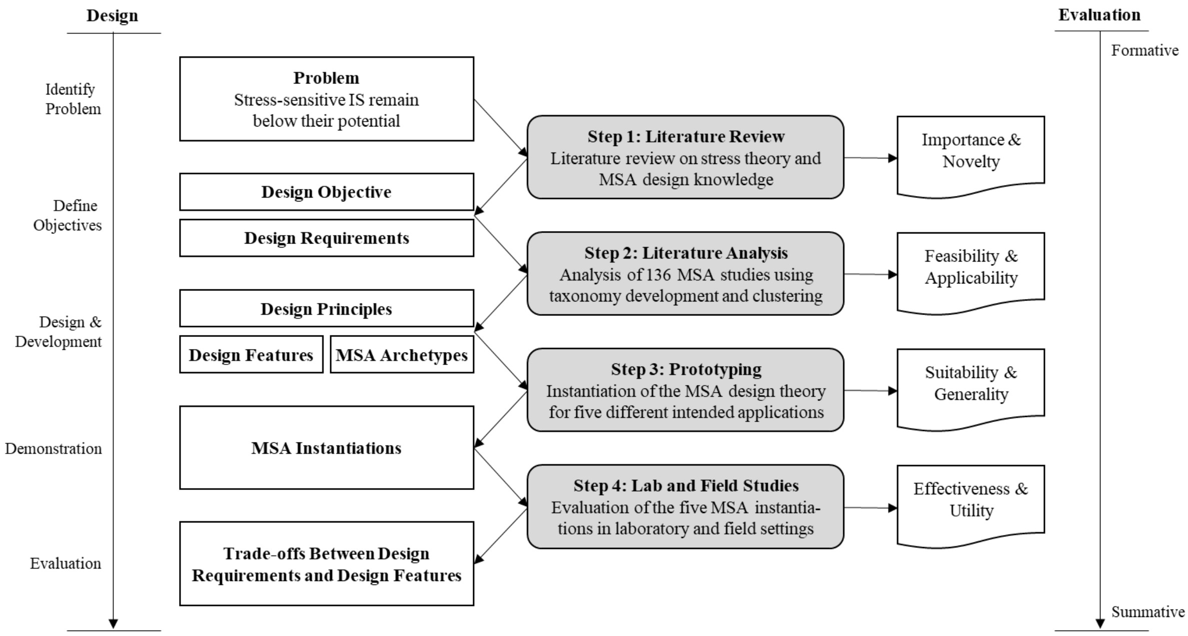


Figure 16: Research Process Building on Peffers et al. (2007) and Venable et al. (2016)

Step 2: Literature Analysis. We perform an extensive, structured literature analysis of extant MSA studies to extract and consolidate (implicit or explicit) design knowledge from these studies. We determine relevant publications using two ways: First, a forward/backward search initialized with the five MSA literature reviews presented in the Theoretical Foundation subsection (Aigrain 2016; Glenn and Monteith 2014; Greene et al. 2016; Þórarinsdóttir et al. 2017; ur Rehman et al. 2015) yields 55 publications. Second, we perform a structured literature search for research articles in the eight journals in the AIS Senior Scholars‘ Basket of Journals and all outlets in the IEEE Xplore database with the search string "stress AND (assessment OR detection OR determination OR recognition) AND (mobile OR smartphone OR technology) AND (human OR people OR user OR individual)" in abstract, title, and keywords. We included only studies since 2010 because stress detection gained substantial attention from that point on and excluded all studies that do not allow mobile use (e.g., stationary medical devices). This search led to 81 additional studies, resulting in a total of 136 MSA studies (Appendix C.1). The analysis of these studies indicates that few explicitly report design knowledge. Thus, MSA design knowledge is highly dispersed and difficult to access for researchers and practitioners engaged in assessing individuals' stress. The observation that few MSA studies build on other studies to inform their design – a significant limitation in current DSR practice (vom Brocke et al. 2020b) – adds to this and substantiates that our design objective (i.e., developing a design theory for MSA systems) is highly relevant and worth exploring.

Overall, we extract multiple design knowledge elements from the literature analysis. We conceptualize a design blueprint built on architectural commonalities of the MSA instantiations. We then analyze literature in multiple iterations to derive seven design principles and six design features from design-related insights of the MSA literature. The split into design requirements, design principles, and design features is inspired by the design theory on Requirement Mining Systems by Meth et al. (2015). The design requirements describe the functional and quality criteria an MSA system should include. The architectural blueprint and design principles describe how MSA systems can meet these requirements conceptually. The design features detail how the design principles can form a specific MSA system and tailor the system to an application purpose. Each design feature can take on different manifestations. Subsequently, we present archetypical MSA systems, which we identified in a cluster analysis investigating the prevailing combinations of design features in the literature. From the literature analysis, overall, we conclude that creating a design theory for MSA systems is feasible and the produced design knowledge is applicable to design and implement effective MSA systems (Venable et al. 2016).

Step 3: Prototyping. Building upon this theory-driven design knowledge base on MSA systems, we collect practical knowledge by developing five MSA instantiations using prototyping (March and Storey 2008) and action design research (Sein et al. 2011). Each of the five prototypes targets a different application purpose and exhibits a specific pattern of design feature implementations. By implementing the prototypes, we evaluate the suitability and generality of our design theory (Venable et al. 2016) for different application purposes and learn that design features and design requirements may conflict with each other and potentially require trade-offs.

Step 4: Lab and Field studies. While the prototype development indicates that instantiating the design theory is possible, it does not yet verify that its instantiation produces effective MSA systems. We test this by employing each prototype in a laboratory or field study, evaluating its effectiveness. The findings substantiate that the design theory provides practical utility by creating effective MSA systems (see the supplementary material to this article for details).

Design of Mobile Stress Assessment Systems

To derive knowledge on our design theory for MSA systems, we aggregate and leverage existing knowledge from 136 MSA studies in three ways: we (1) analyze architectural commonalities of extant MSA instantiations and conceptualize a design blueprint that demonstrates the components and general architecture of MSA systems, (2) derive seven design principles that serve as good practices for designing MSA from the literature knowledge, (3) and investigate which design features MSA instantiations employ to implement the design principles according to an individual use case.

Design Blueprint

From an architectural perspective, the MSA instantiations in our body of literature share many properties. Most notably, they hold the same architectural components. We perceive that a clear description of these components and their interrelation helps a common understanding of MSA. Our literature analysis’s prevailing insight is that MSA systems are socio-technical systems in which a technical part interacts with its social environment. Five components are present in all 136 studies: (A) the user and their environment, (B) data collection via sensor technology, (C) data storage, (D) data pre-processing, (E) data modeling for stress assessment, and (F) reporting of the results. Figure 17 illustrates the design blueprint which interrelates these components. Arrows depict the process flow in the interplay of the components.

(A) User and Environment: As socio-technical systems, MSA systems interact intensively with the user and their environment. This interaction consists of two transitions between the technical and the social part: First, data on the user and their environment provides the basis for stress assessment (Cohen et al. 1983) by indicating stressors and strains (DR 1). Examples are human physiology (Cho 2017; Singh et al. 2011), human behavior (Liao et al. 2005), and environmental conditions (Garcia-Ceja et al. 2016; Lane et al. 2011). Second, the system loops back to the user and their environment, for example, to allow stress management assistance.

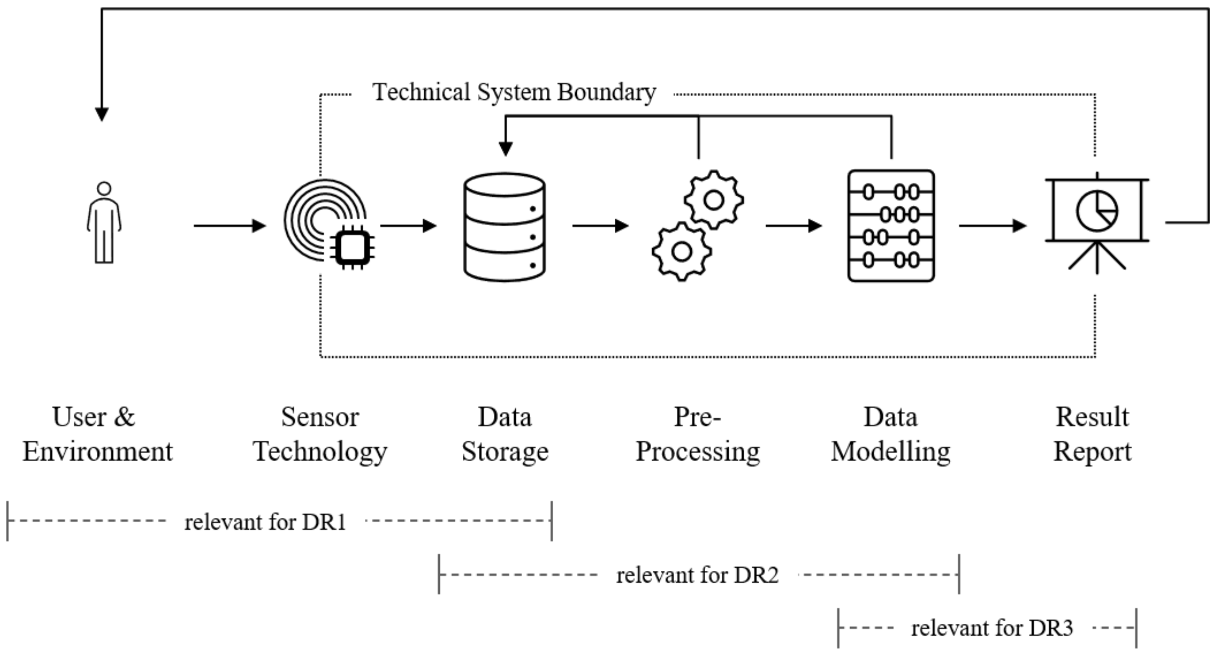


Figure 17: The Architectural Components Forming a Design Blueprint for MSA Systems

(B) Sensor Technology: To gather valid data (DR1), sensors operationalize the first transition from the social to the technical part by collecting the required data. In this view, 'sensor' is every data source that gathers relevant information. Approaches range from self-reported data manually provided by the user to sophisticated sensor fusion models that automatically combine data from various sensors. While approaches building on self-reported data (e.g., periodic questionnaires) are relatively easy to implement, they demand strong user engagement. Consequently, the focal point in current research lies in approaches using hardware (e.g., GPS or microphone) or software sensors (e.g., typing errors or incoming text messages) that automatically collect information on the user and their environment (Gimpel et al. 2015).

(C) Data Storage: The sensor data is stored either locally on the device (Bauer and Lukowicz 2012) or on connected resources such as cloud platforms (Berndt et al. 2011) depending on the particular use case of stress detection (DR2).

(D) Data Pre-Processing: To ensure an appropriate data analysis (DR2), the stored data must be pre-processed because raw sensor data might not be suitable for model generation (Bakker et al. 2011). Typical steps of pre-processing are handling missing data, removing outliers, or aggregating sensor data.

(E) Data Modelling: Statistical model building allows for assessing stress suitably (DR2) building on the pre-processed data (Picard 2003). Here, a broad set of statistical models ranging from simple regressions to sophisticated machine learning approaches can find use.

(F) Result Report: Finally, the system needs to communicate the stress modeling results (DR3) adequately to the user, another system, or a third party (Kennedy and Parker 2019).

Design Principles

Numerous publications in our body of literature describe lessons learned from the design and development of MSA systems. Building on these findings, we derive seven design principles (DPs) providing guidelines for creating MSA systems that satisfy our design requirements. The design principles describe general aspects of MSA system design as principles of form and function (Gregor and Jones 2007) and follow the anatomy of design principles (Gregor et al. 2020) by considering the mechanism of the design principle, its respective context, as well as an aim and rationale for the principle. The design principles support researchers and practitioners as implementers of MSA systems in making essential decisions when designing such systems for users.

DP1 – Consider a wide range of facets of the user and their environment to respect stress diversity. Stress is multifaceted and can originate from psychological (e.g., overload, life events, technology use) as well as physical (e.g., noise, temperature, lighting) stimuli (Lu et al. 2012; Riedl and Javor 2012). Therefore, MSA systems need to capture many facets that may indicate stress (DR1), for example, the user's location history, neurophysiological activity, smartphone or computer usage, medical history, or weather conditions. The literature analysis suggests that a combination of multiple user-related and environment-related facets works best to achieve high stress assessment accuracy.

DP2 – Choose and place sensor technology to meet the requirements for the individual use case. The sensor technology used to implement DP1 constitutes an interface to the user and their environment. Although users do not consciously interact with most sensors, one must design this interface thoughtfully as the sensors may significantly influence an MSA system's user acceptance (DR6) and resource consumption (DR4). Most notably, MSA designers should select sensor technology that corresponds to the individual use case. Also, the placement of sensors is essential. For example, a system enabling MSA for firefighters in action (Sandulescu and Dobrescu 2015) requires different sensor technology than a system assessing stress in daily life (Gjoreski et al. 2015). The first scenario involves special wearable equipment (e.g., a smart shirt) to measure firefighters' stress. In the second scenario, an everyday device (smartphone) is more suitable to collect the data. DP2 also contributes to the production of valid data in line with DR1.

DP3 – Select reasonable query times and intervals for all sensors to provide a basis for reliable stress detection with low obtrusiveness. Physiological markers, for example, respond differently depending on acute or chronic stress. For example, heart rate increases when experiencing acute stress but decreases from chronic stress (Schubert et al. 2009). Different parts of the human brain and body become active in causal and temporal order resulting in delays until stress reactions are measurable. Therefore, DP3 recommends that MSA system designers select sensor query times and intervals focusing on high reliability and accuracy of MSA (DR5). The selection should also consider requirements regarding the system's resource consumption and user acceptance (i.e., DR4 and DR6). An example of a reasonable combination of query times and intervals is a study on stress detection for public bus drivers (Rodrigues et al. 2015). The study combines two different data query modes: random self-reports and continuous physiological measurements. Like DP1 and DP2, DP3 addresses the validity of the collected data and contributes to DR1.

DP4 – Comply with users' routines and habits to ensure high acceptance of the MSA system. Adjacent to DP2 and DP3, which emphasize selecting sensors and query times according to the individual use case, another aspect is vital for high user acceptance: unobtrusively collecting data (i.e., DR1 and DR6). Sensors not requiring the user's active and conscious interaction and not interfering with their routines and habits are always preferable. As stated in the Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al. 2012), habit is positively related to use behavior. Therefore, DP4 proposes to design MSA systems to fit users' routines and habits to allow system usage to become habitual. This routine results in a positive impact on use behavior through acceptance. For instance, Ciman and Wac (2018) developed an MSA approach building on the analysis of smartphone gestures, which are considered routine for most users.

DP5 – Fuse data from multiple sensors to comprehensively grasp the user and their environment. To get a comprehensive view of the user's context, MSA designers should plan which aspects of the user and their environment complement each other for stress assessment

(Adams et al. 2014; Ayzenberg et al. 2012) and combine them by fusing data from multiple sensors. As stress is a complicated part of human life, solely analyzing raw data is not sufficient. Already simple descriptive statistics may provide relevant insights into users' behavior (e.g., deviation of a daily routine, variation of behavior depending on the location). Thus, preprocessing the fused sensor data is essential for stress assessment (i.e., DR2 and DR5).

DP6 – Personalize stress assessment to consider the individual causes and consequences of stress. According to Garcia-Ceja et al. (2016), there are three different ways to model the interrelations between sensor data and stress: building a general model (generalizing data from multiple users), a personal model (using data from single users), or a hybrid combining personalization and a general model. To account for the individual causes and consequences of stress, DP5 recommends using a personal or a hybrid stress model. To implement personalization, MSA systems need to collect data on the user's stress, for instance, through introspective questionnaires (Gimpel et al. 2019a). Patterns in historical stress and sensor data can indicate the presence of stressors or strains and thus serve as a proxy for assessing current stress states (Adams et al. 2014; Bogomolov et al. 2014). Together with DP5, this design principle suggests a way for MSA systems to calculate a suitable result for users' stress levels (DR2).

DP7 – Report a measure of stress to the recipient intuitively and understandably to enable efficient assessment. The final building block of an MSA system is reporting the assessment results to a recipient. DP7 proposes to transparently report an MSA system's calculated stress level to the user, thereby satisfying DR3. Further, the design principle connects to DR5, which requests the algorithms used in an MSA system and, thus, the reported stress measure to be accurate. Also, the reported result must be intuitive and understandable to ensure user acceptance (DR6). However, the recipient mentioned in this design principle does not necessarily need to be the MSA system user. For instance, the MSA system for firefighters in action (Sandulescu and Dobrescu 2015) features a *Remote Processing Unit,* enabling remotely reporting the firefighters' calculated stress measures to the mission supervisor. Thus, the reported stress measure depends on the MSA system's application purpose.

Design Features

While the design principles presented in the previous subsection describe recommendations for MSA system design, they do not provide information on a specific implementation. Therefore, building on our literature analysis, we derive six design features (DFs) illustrating various implementation methods for the respective design principles. Figure 18 shows the mapping of the design features to the respective design principles.

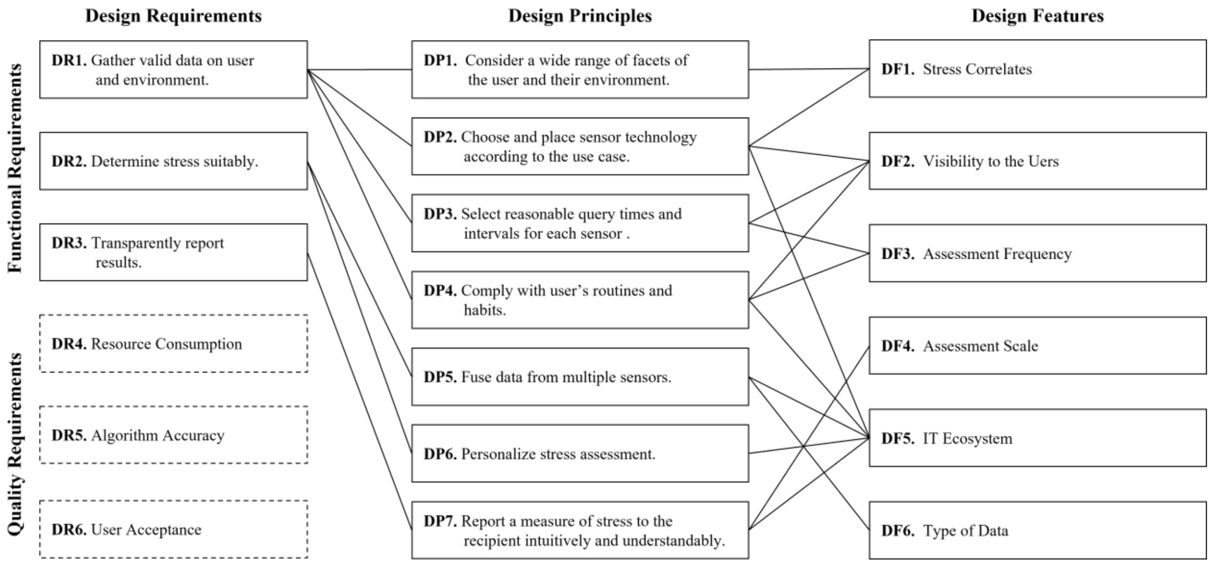


Figure 18: Interdependencies of Design Requirements, Design Principles, and Design Features

DF1 – Stress Correlates. Following DP1, MSA considers both user-related and environmental facets to assess stress. Following DP2, the sensor technology used to collect these facets should align with the MSA system's application purpose. By combining these two design principles, MSA systems may include a variety of *stress correlates*. These stress correlates can be possible causal antecedents, causal consequences, or otherwise associated measures which the MSA system can use to infer the user's stress level. MSA systems can pursue different ways of implementing this design feature. Some systems use *introspection* to prompt the users for input on their stress perception or feelings at specific points in time, for example, by stress diaries (Wang et al. 2014). *Biological symptoms* of stress include all bodily changes associated with automatic biological processes such as heart rate or pupil dilation. *Behavioral symptoms* such as reduced typing accuracy (Gimpel et al. 2015), characteristic gestures (Lefter et al. 2016), or voice modulation (Ferreira et al. 2008) are further common stress correlates. Many systems include *environmental information* such as weather information or ambient noise to improve assessment performance (Mayya et al. 2015) and implement a *mixed form* of stress correlates.

DF2 – Visibility to the Users. Like DP4, our literature analysis revealed that an MSA system could target different levels of *visibility to the users*. This visibility describes the degree to which an MSA system integrates into an individual's life without interfering with the users' routines and habits (DP4). The desired level of visibility to the users also depends on sensor technology choice and placement (DP2) and the selection of query times and intervals (DP3). We identify three levels of visibility to the users. An *obtrusive* way of implementing an MSA system requires the user's attention. Typical characteristics of obtrusive MSA systems are questionnaires (Ferdous et al. 2015) on smartphones to trigger momentary ecological assessments (Chang et al. 2011; LiKamWa et al. 2013). *Unobtrusive* systems do not require the users' attention but still require them to adapt their habitual routines. They often employ long-range devices such as video cameras to assess the stress level (Elgharib et al. 2015). *Life-integrated* MSA systems refrain from altering users' daily routines and seamlessly integrate into these routines. This life integration can be achieved, for example, by using only smartphone sensors for stress assessment (Gimpel et al. 2019b).

DF3 – Assessment Frequency: An MSA system's *assessment frequency* depends on the type of stress an MSA system addresses (i.e., acute or chronic stress). Selecting reasonable query times and intervals (DP3) is an essential prerequisite for implementing a suitable assessment frequency. Further, it is crucial to comply with users' routines and habits (DP4) to ensure the respective assessment frequency's viability. There are three implementations for this design feature. Assessing stress in *regular intervals* of weeks or months is sufficient for long-range assessments (Fehrenbacher 2017). *Continual* stress assessment estimates the user's stress in shorter intervals of a day or less and is required to evaluate the effects of stress interventions targeting chronic stress or investigate extended episodes of acute stress (Wang et al. 2014). *Continuous* stress assessment obtains stress levels in real-time and is used for just-in-time interventions (Nahum-Shani et al. 2015) like stress-sensitive adaptive enterprise systems (Adam et al. 2017).

DF4 – Assessment Scale: The *assessment scale* specifies which requirements the assessment results must meet concerning their granularity level. Implementing a specific assessment scale in an MSA system addresses DP7 to determine what the system reports to the respective recipients. Our literature analysis indicates three methods for implementing this design feature. The easiest way to model stress is a *binary* variable differentiating between 'stress' and 'no stress' (Bogomolov et al. 2014; Chen et al. 2014). Some use cases, however, require a higher granularity level for stress intensity. An *ordinal* scale can satisfy such requirements. For example, Garcia-Ceja et al. (2016) investigated MSA building on smartphone sensor data and a three-level stress scale. *Metric* scales such as the Perceived Stress Scale (Cohen et al. 1983) allow an even more fine-grained differentiation of stress levels (Gao et al. 2014).

DF5 – IT Ecosystem: The design feature *IT ecosystem* specifies the scale of an MSA system's technical implementation. The selection and placement of sensor technology (DP2), complying with users' routines and habits (DP4), and the implementation of sensor fusion (DP5) impose requirements on the IT ecosystem. Further, personalizing stress assessment (DP6) and reporting stress assessment results (DP7) impact an IT ecosystem's scale and architecture. For this design feature, we identify three implementations. The components of an MSA system may operate on a *single device* (e.g., Bauer and Lukowicz 2012; Bogomolov et al. 2014). However, many MSA systems exhibit a distributed system architecture that connects *multiple devices using local communication* protocols (e.g., Liao et al. 2005; Rodrigues et al. 2015). Some use cases require an even more large-scale approach, which connects devices and components via internet-based protocols to form *Multi-Platform-Systems* (Ayzenberg et al. 2012; Berndt et al. 2011; Lane et al. 2011). These systems enable integrating location-dependent sensors in smart homes or wearable biosensors.

DF6 – Type of Data: MSA systems differ in the *type of data* used for stress assessment. As stress is highly individual, its assessment requires collecting detailed user information, causing privacy concerns. Consequently, MSA systems must implement high security and privacy standards (Adams et al. 2014). This design feature relates to the data aggregation level for a comprehensive view of MSA system users and their environment (DP5). We identify three types of data used for stress assessment. If the system collects exclusively *non-personal data* from the environment (Betti et al. 2017), few privacy concerns exist. However, if a use case additionally demands *aggregated personal data* (e.g., number or duration of phone calls), data security and privacy must be increased. The most sensitive type of data in stress assessment is *raw personal data*. This form of data includes, for example, message contents (Ayzenberg et al. 2012) or video data (Cho 2017). MSA systems building on this data, therefore, require high protection standards.

Overall, the six presented design features illustrate various ways of how to implement MSA systems. MSA system designers can reflect on which of these implementations best fit the requirements imposed by their respective use cases. Table 20 summarizes the design features and instantiations derived from the literature.

Design Feature		Manifestations (mutually exclusive, collectively exhaustive)				
DF1	Stress Correlates	Environment (0)	Introspection (2)	Biological Symptoms (62)	Behavioral Symptoms (22)	Mixed (50)
DF2	Visibility for the User	Obtrusive (45)	Unobtrusive (78)	Life-integrated (13)		
DF3	Assessment Frequency	Regular Intervals (36)	Continually (56)	Continuously (44)		
DF4	Assessment Scale	Binary (67)	Ordinal (54)	Metric (15)		
DF5	IT-Ecosystem	Single Device (18)	Multiple Devices using Local Communication (72)	Multi-Platform-System (46)		
DF6	Type of Data	Non-Personal Data (7)	Non-Personal and Aggregated Personal Data (89)	Non-Personal and Raw Personal Data (40)		

Note: The numbers in parentheses refer to n = 136 publications on MSA and indicate how many of the identified systems exhibit the given characteristic.

Table 20: Ways of Implementing the Design Features

Mobile Stress Assessment System Archetypes

The design knowledge presented in the previous subsection reveals valuable insights into MSA design by producing general design principles and specific design features as levers that help tailor the system to its application purpose. To achieve higher-level insights into current MSA systems' diversity, we investigate the characteristics of extant MSA studies in more detail. Using divisive hierarchical clustering, we identify overarching archetypes of MSA systems according to their design features. The elbow method (Thorndike 1953) suggests a five-cluster solution. Table 21 presents archetypes and their footprints showing the archetype's prevailing characteristic in the design feature classification (i.e., at least half of the systems in the archetypes show this characteristic; "n.c." indicates that there is no dominant characteristic). The blue marking indicates that this characteristic is distinctive for the archetype.

	MSA System Archetypes				
	Data-Sparse Assessment (DS)	Sensor-Enriched Assessment (SE)	Wearable-Focused Assessment (WF)	Multi-Facet Assessment (MF)	User-Focused Assessment (UF)
Number of Studies	48	48	6	23	11
Stress Determinants	Biological Symptoms	Biological Symptoms	Biological Symptoms	Mixed	Behavioral Symptoms
Sensitivity of Data	Non-Personal and Aggregated Personal Data	Non-Personal and Raw Personal Data	Non-Personal and Raw Personal Data	Non-Personal and Raw Personal Data	Non-Personal and Raw Personal Data
Visibility for the User	Unobtrusive	Obtrusive	Unobtrusive	Life-Integrated	Unobtrusive
Assessment Frequency	n.c.	n.c.	Continually	Continually	Continually
Assessment Scale	n.c.	Binary	Metric	Ordinal	Binary
Ecosystem	Multiple Devices	Multiple Devices	n.c.	Multi-Platform	Single Device
Examples	Ahmed et al. (2015); Attaran et al. (2016); Cernat et al. (2017)	Chen et al. (2014); Wu et al. (2019); Momeni et al. (2019)	Boateng and Kotz (2016); Anusha et al. (2020); Momeni et al. (2019)	Ciman et al. (2015); Dobbins and Fairclough (2019); Gimpel et al. (2019b)	Rachuri et al. (2010); Ciman and Wac (2018); Ashok et al. (2016)

Table 21: MSA System Archetypes

Data-Sparse Assessment. More than one-third of the analyzed systems have been clustered into this archetype. It is the only archetype that uses and stores personal data only in aggregated form to take care of user privacy. It primarily collects data via additional devices analyzing biological symptoms and storing the results. The system acts primarily unobtrusively and does not actively interact with the user. Examples include Ahmed et al. (2015), who focus on respiratory patterns in stressful and relaxed situations, Attaran et al. (2016), who combine different parameters from a self-developed physiological tracker, and Pandey (2017), who uses IoT devices to inform users about an unhealthy lifestyle and even alerts before any acute condition occurs.

Sensor-Enriched Assessment. Another third of the systems do not place high demands on the system's unobtrusiveness. Instead, users actively interact with the MSA system and may need to adapt their behavior. These systems primarily collect and store data via additional devices.

Compared to the first archetype, a binary classification into “stressed” and “not stressed” states is paramount. Many of the systems in the sensor-enriched assessment archetype aim to be as accurate as possible, use many different sensors from various devices, and are mainly employed in laboratory settings. Examples include Chen et al. (2014), who use a mobile spectrograph to capture hyperspectral imaging data to measure oxygen levels and then infer stress levels, Wu et al. (2019), who attach textile electrodes to a shirt and then use measures such as skin conductance and heart rate variability to determine the users’ stress level, and Cernat et al. (2017), who also use the same two parameters as stress correlates and collects data on car drivers connected to different instruments.

Wearable-Focused Assessment. Few systems focus on the use of wearables for data collection. Systems of this archetype require the user to wear additional devices to collect data unobtrusively, use metric scales to deliver detailed stress levels, and, consequently, tend to be less accurate. Examples of this are Boateng and Kotz (2016), who use a wearable platform to extract data from a commercial heart-rate monitor and determine a stress level continuously and in real-time, Anusha et al. (2020), who use a wrist wearable to record the condition of a physician during an operation, and Momeni et al. (2019), who record and process physiological data as part of a simulator for search and rescue operations.

Multi-Facet Assessment. Systems of this archetype typically combine different stress correlates. In addition to the recognition of biological symptoms, they usually include data on the user’s behavior, environment, and other contextual information. These systems primarily determine the stress level on an ordinal scale (e.g., “no stress,” “low stress,” or “high stress”) and tend to place high demands on the integration into the user’s daily routines without needing them to adapt their behavior. Examples include Ciman et al. (2015), who extract usage data from a smartphone (e.g., tap, scroll, swipe), Dobbins and Fairclough (2019), who collect various data points from drivers, and Gimpel et al. (2019b), who extract various sensors from a smartphone (e.g., GPS, text sentiment, number of calls) to infer stress from data on the user and their environment.

User-Focused Assessment. Distinctive for systems of this archetype is a focus on behavioral changes occurring in stressful situations. Therefore, these systems typically record how users interact with their devices (e.g., smartphones or computer peripherals) and identify stress levels from changes in the interaction. The user-focused assessment archetype particularly aims at unobtrusive stress assessment and typically builds on a single device to collect, store, and process required data. Examples for this archetype are Rachuri et al. (2010), who use data from the smartphone and extract various parameters from the voice to infer the user's emotional state, Ciman and Wac (2018), who analyze touchscreen operation in their prototype, and Ashok et al. (2016), who extract sound from a microphone to quantify stress in the human body using voice analysis.

Trade-Offs for Implementing Mobile Stress Assessment Systems

The findings presented in the previous subsections strongly build on extant MSA literature. To gain practical experience, we prototypically designed and developed five different MSA systems. Four prototypes use typical smartphone sensors to assess stress with a general model using multiple sensors (Prototype 1), stress with a personalized model using multiple sensors (Prototype 2), pupil dilation as a stress marker derived from video analysis (Prototype 3), and sleep behavior as stress marker determined from multiple sensors (Prototype 4). Prototype 5 implements an abstract multi-device data collection framework for sensor systems to assess stress or other phenomena. The prototypes address different stress correlates, thereby using different ways of visibility for the user, assessment scales, and IT-ecosystems. We provide a detailed description of the five prototypes and the respective studies in the supplementary material to this article. During the implementation of the prototypes, we were confronted with challenges that required trade-offs between design features and design requirements. Table 22 illustrates which design features and system quality requirements might conflict. An "x" indicates that a trade-off between a manifestation of the design feature and the respective system quality requirement may be necessary.

Design Feature		DR4 – Resource Consumption	DR5 – Algorithm Accuracy	DR6 – User Acceptance
DF1	Stress Determinants	x	x	x
DF2	Visibility to the User		x	x
DF3	Assessment Frequency	x	x	x
DF4	Assessment Scale		x	
DF5	IT Ecosystem	x	x	x
DF6	Type of Data		x	x

Table 22: Trade-offs Between the Design Features and System Quality Requirements

DF1 Trade-offs. An MSA system only capturing self-reported stress will not provide accurate results if a physiological stress marker is unknown to the user. A mixed approach (i.e., a combination of data originating from the users' environment, introspections, physiology, or behavior) may increase algorithm accuracy (DR5). The gathered data covers different facets of stress, thus creating a more holistic picture. However, an MSA system's technical resource consumption might increase when using a mixed approach due to additional data processing and analysis (DR4). Thus, one should only consider a mixed approach if the individual use case allows for higher resource consumption. Using a mixed approach might imply lower user acceptance because more data must be gathered and evaluated (DR6).

DF2 Trade-offs. The MSA system's visibility to the user (i.e., the grade of obtrusiveness) implies trade-offs between DF2 and the design requirements. The more obtrusive the MSA system is to the user, the more the accuracy of the used algorithms might be affected (DR5). If the users are intensely distracted by the system's obtrusiveness, this might create a bias in assessing the users' stress. Under exceptional circumstances, the system's obtrusiveness could become a stressor for the user and corrupt the results. In addition to algorithm accuracy, determining an MSA system's visibility also affects user acceptance (DR6). When assessing Prototype 1 on life-integrated stress assessment, we found that a high integration level is vital for an MSA system's high user acceptance. However, one can hardly achieve life integration of an MSA system with zero obtrusiveness. Therefore, the goal is to reduce the system's visibility as much as the application purpose admits. When the purpose is to provide biofeedback, the complete system (combining assessment and feedback) cannot be unobtrusive.

DF3 Trade-offs. Determining the assessment frequency of an MSA system affects each of the properties addressed by the presented system quality requirements of moderate resource consumption (DR4), algorithm accuracy (DR5), and user acceptance (DR6). An MSA system featuring a high assessment frequency will require more technical resources than systems with a moderate or low assessment frequency. In the context of testing our Prototype 1, we experienced that high sensor query rates resulted in an excessive discharge of the mobile devices' batteries. In contrast, a high assessment frequency results in more accurate assessment results due to a better measurement database. One way to mitigate this conflict might be to use high assessment frequencies in the initial phase of system usage to build a solid base of measurement data and lower assessment rates to reduce resource consumption. Assessment frequency also affects user acceptance. In this context, the technical level is less relevant than the system directly prompting the user to make inputs for personalization purposes. In evaluating Prototype 2 on mobile personalization of stress assessment, we discovered that an MSA system's personalization should be as passive as possible. After achieving a sufficiently high personalization level, requesting user input should be reduced to ensure user acceptance in the long run.

DF4 Trade-offs. Choosing the assessment scale has implications for the algorithm accuracy of an MSA system (DR5). Using a continuous stress scale, algorithm accuracy can generally be increased over a binary scale since it can represent more nuances in the assessment results. However, a high variance in the results can cause a lack of reliability. In specific use cases, a binary classification might be sufficient. For instance, evaluating our prototypical framework for automated data collection, storage, and preprocessing showed satisfying results for binary assessment. Overall, selecting a suitable assessment scale depends on the use case and does not interfere with other system quality requirements except algorithm accuracy.

DF5 Trade-offs. As for the assessment frequency, the specification of an IT ecosystem for the MSA system affects each of the properties addressed by the system quality criteria DR4, DR5, and DR6. The MSA system's resource consumption increases as the IT ecosystem grows in scale and complexity. However, depending on the use case, a larger IT ecosystem may be an essential prerequisite for stress assessment. Therefore, technical resource consumption should not be considered a general limit to the used IT ecosystem's size. The scale of the IT ecosystem may also have an impact on algorithm accuracy. For example, integrating sensor fusion into an MSA system implies a higher complexity of the IT ecosystem but may increase algorithm accuracy. In evaluating Prototype 4 on sensor fusion for sleep duration assessment, we could achieve a high classification accuracy greater than 90 percent. The scale of the IT ecosystem also has implications for user acceptance. System architectures proposing to store assessment results in the cloud might raise privacy concerns, resulting in decreased user acceptance.

DF6 Trade-offs. The type of data used in an MSA system can affect algorithm accuracy (DR5). The more individualized the collected data is, the better its insight into the users' internal condition (e.g., physiological markers, self-reports). However, collecting sensitive data often results in privacy concerns and decreased user acceptance (DR6). Prototype 1 recorded and analyzed the content of received and sent text messages to detect stress signs. However, this caused considerable privacy concerns among the users, so we stopped storing the contents and processed them in coded form after an on-device analysis. Overall, user privacy should be highly prioritized, but trade-offs are required to achieve high algorithm accuracies.

Discussion

The previous subsections presented interrelated knowledge on how to design MSA systems. Six design requirements specify the purpose and scope of MSA systems. A design blueprint illustrates typical architectural components. Seven design principles emphasize important considerations in designing MSA systems. Six design features guide the tailoring of MSA systems to their specific application purpose. Each of these elements enriches the design knowledge base (vom Brocke et al. 2020b) on MSA design. Together, however, they form a mid-range theory for design and action (Gregor 2006; Gregor and Hevner 2013), which needs to be applied and validated within the research community.

The design theory adds to current literature on MSA by providing a comprehensive knowledge base and structure for the design of MSA systems. In presenting the design theory, we follow the structure of IS design theories proposed by Gregor and Jones (2007). They suggest that researchers should describe a design theory with eight components. According to this structure, our design objective and design requirements specify MSA systems' *purpose and scope*. The design blueprint and principles constitute the *principles of form and function* describing MSA systems' general architecture and design. The design features and MSA system archetypes serve as *principles of implementation*. Table 23 provides further details on the composition of the design theory for MSA systems.

We compiled and evaluated the design theory and its design knowledge in four methodological steps. First, an ex-ante literature review provided insights into the general design requirements and the diversity of MSA systems. It substantiated the novelty and importance of our research (Sonnenberg and vom Brocke 2011). Second, a structured literature analysis consolidated design-related insights from 136 MSA studies and laid the foundation for developing the design blueprint, the design principles, and the design features. A supplementary cluster analysis reveals five archetypes of MSA systems that are currently prevailing. Altogether, this step demonstrated that the development of MSA systems is feasible and that the design knowledge presented here applies to MSA system development. Third, the development of five own prototypes substantiated this claim and showed the design knowledge's suitability and generality for creating diverse MSA systems with different application purposes (Sonnenberg and vom Brocke 2011; Venable et al. 2016). Further, the prototyping produced additional design knowledge in the form of trade-offs that need to be made between the quality-related design requirements and the design features' implementations. Fourth, the prototypes' evaluation in lab and field studies provides summative real-world evidence of the design knowledge's applicability and utility for developing effective and suitable MSA system instantiations (Sonnenberg and vom Brocke 2011; Venable et al. 2016).

Component	Description
Purpose and scope	MSA systems aim to assess an individuals' stress level from data on the individual, their environment, and their interactions with the environment. The design is applicable for all use cases and characteristics within the presented range of design requirements.
Justificatory knowledge	The design theory builds on well-established long-standing theories on stress in the social sciences with application in IS research, especially the Transactional Model of Stress by Lazarus and Folkman (1984). Further, the design theory relies on a body of research on stress sensing and affective computing in computer science and IS research.
Constructs	Core constructs for the design are 'stress,' 'stressor,' 'strain,' 'mobile stress assessment,' and 'sensor' (subsection Theoretical Foundation).
Principles of form and function	Our design blueprint and the design principles guide MSA system designers in elaborating a design that satisfies the general design objective and design requirements. Consequently, we propose both elements to constitute the abstract functional design for MSA systems.
Principles of implementation	The design features' implementation is specific to the MSA system's use case. Thereby, the design features enable the adaptation of the general design to the specific application purpose.
Expository instantiation	Our prototypes implement the design blueprint, follow the proposed design principles, and adapt the design to an individual use case using the design features. With our prototypes, we evaluated the design theory's effectiveness and operationality.
Testable propositions	We claim that well-designed and implemented mobile systems following our design blueprint and principles can assess an individual's stress level. Our prototypical instantiations support and future research may further test this claim. We also claim that omitting core components of the design blueprint or disregarding design principles will significantly decrease the quality of an MSA system to be designed.
Artifact mutability	The domain of mobile devices and affective computing is subject to constant and continuous change. Our design theory enables a reaction to these changes. It can include wearables and smartwatches as valuable data sources once they become widely distributed and accepted or respond to future communication trends such as social media platforms. The design knowledge on MSA systems might also apply to new methods and models for data analysis and transformation.

Table 23: Compilation of a Design Theory for MSA Systems Following Gregor and Jones (2007)

Naturally, our work is subject to limitations. First, although 136 studies are a substantial amount, we did not search all outlets of IS and adjacent disciplines for knowledge on MSA. Also, our literature analysis considered only studies published as of 2010 and thus might have neglected early works on MSA. Broadening the scope of the studies included might produce additional insights into good practices in MSA system design. Second, although we developed prototypes for various use cases, the possible applications of MSA systems are manifold, and we could only consider a small subset here. Also, we did not turn each of the presented archetypes into a prototype. Developing additional prototypes might thus reveal that more trade-offs might be necessary. Third, we set our focus on MSA but did not yet build the bridge to ICT-assisted stress interventions, for example, in the context of stress-sensitive IS (Adam et al. 2017; Friemel et al. 2017; Jimenez and Bregenzer 2018).

Our design theory connects and complements the findings of five reviews on MSA literature which we considered at the outset of our research. Other than the work of Þórarinsdóttir et al. (2017), ours is not limited to self-assessed stress but also considers external measures of stress. Aigrain (2016), Greene et al. (2016), and Glenn and Monteith (2014) described exemplary components of MSA systems, including algorithms, sensory devices, or project settings, which build the foundation of our holistic perspective on MSA systems. We drew specific information regarding the mobility dimension of MSA system design from ur Rehman et al. (2015), who delivered a comprehensive review on the use of mobile devices for mining personal data.

Overall, the design theory presented here expands on extant MSA literature by producing and consolidating relevant design knowledge from design-related learnings in 136 studies. We tested and extended it in the scope of our prototyping activities (vom Brocke et al. 2020b). Overall, the design theory enriches MSA literature by providing researchers and practitioners with comprehensive design knowledge on MSA systems.

The implications for research are manifold. Future research may use our design theory to build stand-alone MSA systems to study their design, use, and effectiveness. Likewise, our theory may inform the development of stress management systems that have an MSA component. For researchers building MSA systems, our theory may improve their development efficiency as they can draw on the knowledge base. Using the accumulated design knowledge may also improve the effectiveness of future MSA systems. Finally, future research should test and expand our design theory. Expansion appears most promising with increasing innovation in sensors, devices, and machine learning algorithms which may eventually lead to more effective MSA systems. The large number of MSA systems reported in recent literature (136 systems we identified since 2010) shows the research interest in MSA systems and the demand for MSA system design knowledge.

The implication to practice is that the design requirements, the blueprint, the design principles, design features, and the trade-offs may be used by system designers for creating MSA systems and stress management systems featuring MSA.

Conclusion

The research in this section follows various calls for intensified efforts on developing technical solutions to mitigate individuals' stress (Adam et al. 2017; Friemel et al. 2017; vom Brocke et al. 2020a) and contributes to IS design research by composing a design theory for MSA systems. The design theory builds on knowledge from 136 MSA studies and our own experience resulting from implementing MSA system prototypes. It connects design requirements, a design blueprint, design principles, and design features as design knowledge elements obtained from analyzing extant MSA studies. We complement this theory-driven design knowledge by presenting relevant trade-offs between design requirements and design features that we encountered during the development of five prototypes for different application purposes.

Future work may leverage our design theory to build MSA systems more efficiently and more effectively. Going beyond MSA, future work should link stress assessment to stress management interventions, for example, in the context of stress-sensitive IS (Adam et al. 2017; Friemel et al. 2017; Jimenez and Bregenzer 2018). However, it is not clear that a technological solution for stress assessment is the most appropriate solution because technology itself is a potential stressor. However, we contend that it is worth exploring and evaluating how mobile sensing and assessment can support stress management.

5.3. Towards Designing an Assistance System for Coping with Stress

Effective mobile stress assessment, as elaborated in the previous section, can provide the basis for more sophisticated digital assistance. Examples from other domains than stress show that ICTs can act as health behavior change support systems that use mobile sensor data to help individuals stay motivated with healthy behavior like regular physical activity, smoking cessation, or a balanced diet (Oinas-Kukkonen 2013). An HBCSS is a health-related "socio-technical information system with psychological and behavioral outcomes designed to form, alter or reinforce attitudes, behaviors or an act of complying without using coercion or deception" (Oinas-Kukkonen 2013, p. 1225). Recent literature suggests that HBCSS may assist individuals in changing their responses to stress by facilitating effective coping behavior. While various studies already examined ICTs' potential to determine the user's stress for the purpose of self-reflection (Carter et al. 2019; Sanches et al. 2010) and first efforts have been made towards informing users' self-regulation by providing detailed feedback on potential sources of their stress (Bavaresco et al. 2020), some scholars propose further steps to support individuals' coping with stress enabled by sensor data. They suggest that IS should recommend targeted emotional and behavioral strategies for coping with stress (e.g., relax, seek support) (Adam et al. 2017; Reimer et al. 2020) or automatically execute technological actions to prevent stressful situations (e.g., turn off notifications, delegate community tasks) (Adam et al. 2017). Although these studies reinforce that the development of an HBCSS dedicated to improving individuals' coping behavior is worth exploring, to the best of our knowledge, the question of how to design an individual IS which assists their users in coping with stress based on multimodal sensor data is yet open to research. Thus, combining these proposals, we construct the vision of a mobile coping assistant (MoCA) that exploits the sensing capabilities of mobile devices to support individuals' stress coping by facilitating a sustainable behavior change and preventing the occurrence of stress. Consequently, our study pursues the objective: *elaborate the design of a mobile app for everyday use that uses multimodal sensor data to support its user cope with daily stress.*

Our research follows standard design science methodology and evaluation guidelines (Hevner et al. 2004; Sonnenberg and vom Brocke 2012). It builds upon stress theory and an analysis of mobile apps and studies on mobile stress coping support and explores how to design a system providing just-in-time coping support. Our design comprises the architecture of a MoCA, good practices for designing the architectural components, and an algorithm for selecting coping activities based on data on the user's behavior, characteristics, preferences, and environment.

The remainder of this section is structured as follows: The first subsection describes the methodological procedure of our research. The second subsection presents an analysis of mobile apps and studies on mobile stress coping support. The third subsection presents the resulting design and prototype. The fourth subsection discusses contributions and implications. The fifth subsection concludes.

Methods

Our design science research project (Hevner et al. 2004) strives to elaborate the design of a MoCA assisting individuals in coping with stress based on multimodal sensor data. It follows the build and evaluate cycle by Sonnenberg and vom Brocke (2012) and integrates evaluation activities (Eval1-4) directly into the research process.

As a first step, we identified a problem in the lack of a design proposition on how a MoCA could be instantiated. Various prior works support the claim that there is a need for more powerful mobile coping support and indicate promising design requirements (Eval1) (Adam et al. 2017; Reimer et al. 2020). In the second step, we iteratively designed the MoCA, building on an extensive analysis of mobile apps and studies in the context of mobile coping support (Eval2). We searched the multidisciplinary Scopus database for articles reporting an "application," "app," "tool," or other "mobile" solution associated with "stress coping" or "stress management" and included additional finds from adjacent searches. We selected relevant articles first by screening titles and abstracts and then by reading the articles. This process yielded four comprehensive reviews of mobile apps available through the Google and Apple app stores (Coulon et al. 2016; Harrison et al. 2011; Kennedy and Parker 2019; Lau et al. 2020) and another 38 individual studies on mobile coping support. In the first iteration of our iterative design process, we derived a typical architecture of MoCAs and identified vital architectural components. In the second iteration, we extracted good practices on what to consider in designing these components. The third iteration produced an algorithm for selecting adequate coping recommendations and actions with respect to the user, the cause of their stress, and the context. To test the design, we developed a prototype (Eval3) instantiating MoCA's elementary architecture and providing advanced stress coping support by pointing the user to potential stressors in their behavior and environment. These prototyping activities and their testing suggest that the instantiation of a MoCA is feasible and give first indication of the design's utility to produce effective MoCA systems. Future iterations of the prototype will include the provision of coping recommendations and automated execution of actions targeting to prevent stressful situations. A real-world evaluation of MoCAs' applicability and effectiveness in the field (Eval4) is yet open to future research.

Analysis of Mobile Apps and Studies on Mobile Coping Support

Naturally, our research takes inspiration from similar apps and studies. Our literature analysis reveals that many approaches to mobile stress coping support exist. We divide them into three categories: 1) mobile apps assisting their users in coping with stress without collecting continuous information on their stress level, 2) studies assessing single symptoms of stress and delivering feedback to the user to motivate coping, and 3) mobile apps using many sensors to identify stressors and symptoms and provide an advanced understanding of the stressful situation's context.

Many stress management apps available through the Google and Apple app stores belong into the first category (Coulon et al. 2016; Lau et al. 2020). Here, a multitude of apps provides general educational information and training on stress coping (e.g., Ebert et al. 2016; Sanches et al. 2010) with an emphasis on meditation, mindfulness, and other relaxation strategies. Apps in this category typically offer either on-demand coping knowledge and exercises to tackle acute stress (e.g., Harrison et al. 2011; Hwang and Jo 2019) or accompany organized programs to train coping skills (e.g., Ebert et al. 2016), for example, by encouraging daily tasks (Carter et al. 2019). Despite evidence for their general effectiveness (Ebert et al. 2016; Hwang and Jo 2019), a recent review of stress management apps investigated the apps' contents and found that few apps reinforce regular coping activity, which is required for a sustainable behavior change (Payne et al. 2016), in particular when individuals are busy. Consequently, various scholars emphasize gamification and other behavior change techniques dedicated to keeping users engaged with using the app (Carter et al. 2019; Christmann et al. 2018; Hoffmann et al. 2017). An interesting approach that falls out of the typical pattern in this category was described by McDaniel and Anwar (2017), who describe a mobile app that delivers coping recommendations on demand based on user input on the specific stressful situation. Although the systems in this category do not suffice our MoCA definition because they do not collect sensor data, this research stream demonstrates that mobile systems are a valuable (Morrison et al. 2018), effective (Ebert et al. 2016; Hwang and Jo 2019), and desired (Proudfoot et al. 2010) approach to support individuals' stress coping and that the inclusion of techniques to reinforce coping behavior (Hoffmann et al. 2017; Payne et al. 2016) is crucial.

Studies in the second category use physiological or psychological measures to evaluate bodily stress symptoms and provide biofeedback. This mind-body intervention externalizes the physiological state and allows the user to monitor changes in real-time (Schwartz 2010). Many studies in this domain use a single sensor as an indicator for stress. In mobile settings, the most frequently used measures relate to heart rate (Al Osman et al. 2016; Gaggioli et al. 2014) or skin conductance (Sanches et al. 2010; Winslow et al. 2016) as psycho-physiological stress indicators. A recent systematic review of biofeedback studies in stress management (not limited to mobile use) discussed that biofeedback may effectively support individuals coping with stress (Yu et al. 2018). However, time and practice are required to develop the needed self-regulation competencies (Yu et al. 2018). Another review on the topic found that biofeedback seems to be more effective in reducing stress for individuals who are used to operate under stressful conditions than for convenience-sampled populations (Kennedy and Parker 2019). These findings suggest that biofeedback may trigger self-reflection (Sanches et al. 2010) but struggles to initiate a sustainable behavior change, especially when individuals do not regularly experience high stress.

To facilitate stress-related self-regulation, a better understanding of the stressed individual’s situation might be helpful. Hence, the third category of related studies focuses on collecting multimodal data on the user and their environment to determine potential stressors. In this vein, several studies produced mobile apps that assess stress using various smartphone or wearable sensors (Gimpel et al. 2019b; Wang et al. 2014). This sensor data may allow painting a clearer picture of the stressful situation by investigating stressors and symptoms based on contextual data such as the current time, weather, ambient noise, or the user’s location, physical activity, or messaging behavior (Gimpel et al. 2019a). To facilitate everyday use, some apps target the unobtrusive or life-integrated assessment of stress (Gimpel et al. 2019b) using only sensors which do not require the user’s attention. To date, most of these efforts end with the assessment and reporting of stress based on multiple sensors. Few studies take the next step and deliver the broader context of the situation or targeted coping recommendations. One of few notable exceptions is Bavaresco et al. (2020), who assess stress based on physiological measurement and use various sensors to determine the user’s basic activity (e.g., standing still, walking, in a vehicle) in the case of stress. Similarly, Alharthi et al. (2019) and Reimer et al. (2020) collect further contextual data (time, location, weather) to suggest just-in-time relaxation exercises in the case of stress. The latter two studies additionally stress the importance of properly timed interventions to prevent counteracting effects potentially resulting in increased instead of decreased stress. While they constitute valuable proofs-of-concept that just-in-time recommendations can assist individuals’ coping, they do not exploit coping recommendations’ full potential by evaluating why the user might be stressed.

Overall, this analysis revealed that several approaches to mobile coping support aiming at different levels of user support exist.

How to Design and Implement MoCAs

Design Requirements

To further specify what constitutes a MoCA, we develop a set of design requirements. Several design requirements derive from the objective to design a mobile app that supports individuals cope with stress using multimodal sensor data. The analysis of existing solutions for mobile coping support presented in the previous subsection demonstrates that different levels of support are conceivable. From the literature, we learned that reinforcing elements are important to motivate users to use the MoCA regularly and foster a sustainable behavior change. Also, MoCA should factor in individual (e.g., age, preferences, mental health) and contextual characteristics (e.g., time, location, ICT use) when recommending or taking coping actions. Additionally, the interventions' timing needs to be well-considered.

Further inspiration for the design of coping support is taken from a recent study by Adam et al. (Adam et al. 2017). They proposed the abstract design of a corporate information system that uses sensors to assess employees' stress and takes purposive interventions utilizing individual, technological, and organizational levers. The study presents an implementation roadmap comprising four stages of coping support at incremental levels of support. Since their envisaged system targets stress in a defined work environment, the roadmap needs to be adapted to fit the setting of MoCA supporting an individual in coping with work and personal stress. Both settings are comparable in the way that a single system (enterprise or mobile system) accompanies the user throughout the considered period of time (working day or entire day), assesses stress, and acts accordingly. Yet, two changes are necessary: First, the original roadmap features a stage involving organizational interventions. However, organizational interventions are not available to MoCA since there is no organization involved. Second, given the broader range of stressors in MoCA (due to the inclusion of private hassles and conflicts), the original roadmap lacks specificity regarding different maturity levels of stress feedback. Systems can either provide feedback on the stress level or only or deliver advanced analytics of why the person might be stressed. After these changes, we distinguish four incremental stages of implementing a MoCA with different interventions:

Stage 1 (*stress reporting*): the system determines the user's current stress level and reports it to the user.

Stage 2 (*stress understanding*): the system comes with increased analytical capabilities and delivers a more detailed understanding of why the user might be stressed based on patterns found in the sensor data.

Stage 3 (*coping recommendations*): the system determines and recommends coping strategies appropriate in the user's specific stress situation (e.g., seeking support with a complex task or taking a break to regain emotional strength).

Stage 4 (*automated coping support*): the system takes automated technological action to prevent the user from stressful situations (e.g., eliminate interruptions from notifications, reprioritize messages) within a user-defined scope of action.

From the defined scope and theoretical underpinning, several design requirements (DRs) for MoCA derive (Table 24). An effective MoCA provides interventions that help reduce the user's stress. A useful MoCA additionally induces a change of coping behavior and advances the user's coping skills.

DR		Stages
1	MoCA must continuously assess the user's stress based on sensor data	1-4
2	MoCA must facilitate just-in-time intervention when it detects elevated stress	1-4
3	MoCA must include reinforcing elements to motivate a sustainable behavior change supporting coping	1-4
4	MoCA must collect multimodal data on the user and their environment to determine stressors, symptoms, and context	2-4
5	MoCA must deliver coping actions and recommendations that fit the user, their preferences, and context	3-4
6	MoCA must execute targeted technological actions to prevent stressful situations	4

Table 24: Design Requirements of a Mobile Coping Assistant

Architecture

As an important element of design knowledge, we derive a general architecture for a stage 4 MoCA from analyzing the related apps and studies (subsection Analysis of Mobile Apps and Studies on Mobile Coping Support) with respect to their architectural backbone. The resulting architecture expands the architectural blueprint targeting stage 1 MoCA, or mobile stress assessment (section 5.2), to include the other stages and is presented in Figure 19.

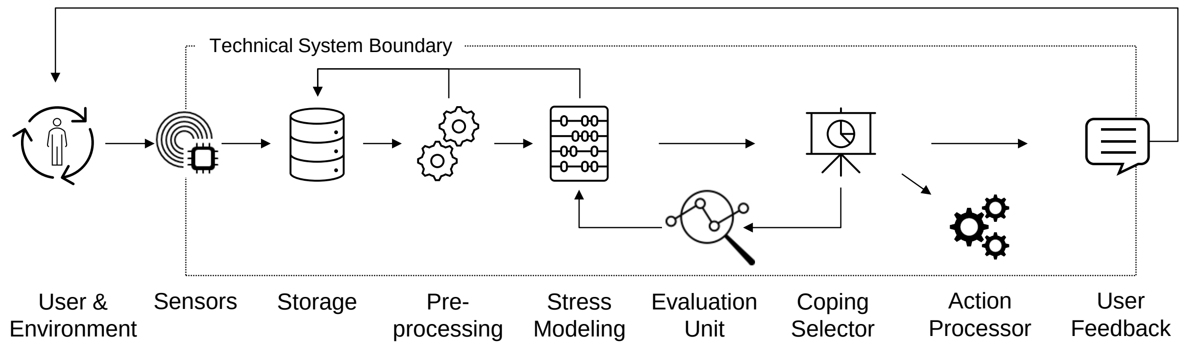


Figure 19: General Architecture of a Mobile Coping Assistant

The architecture conceives a MoCA as a socio-technical system in which the technical part closely interacts with its social environment, represented by the assistant's *users and their environment*. The MoCA uses various *sensors* to collect data on this social environment. This data is *stored* and *pre-processed* to obtain a valid and reliable database suitable for subsequent analysis. The first step of the analysis, *stress modeling*, uses the collected sensor data to assess the user's stress level. While this first analysis is sufficient to provide basic stress feedback to the user (stage 1 MoCA), the deeper understanding of the stressful situation (stage 2), the derivation of coping recommendations (stage 3), and the automated processing of preventive technological actions (stage 4) require further analysis. Therefore, the *coping selector* analyzes which coping recommendations and technological actions might apply to the current individual and situational characteristics. The *user feedback* presents the coping recommendations to the user. The *action processor* executes technological actions within the user-defined scope of action and the *evaluation unit* assesses the MoCA's performance and informs model refinement.

The following paragraphs provide good practices on how to design these architectural components:

Sensors: Sensors represent the interface between the technical and the social part of the system. They collect data on the user's behavior (e.g., social interactions, daily activities; Harari et al. 2017), physiology (e.g., heart rate, skin conductance; Kennedy and Parker 2019), psychology (e.g., mood, cognition), and environment (e.g., weather, location; Peternel et al. 2012). Different devices may be used to sense these measures (e.g., smartphones, wearables, sensory hardware such as electroencephalography headbands or sweat pads) (Peake et al. 2018). Sensor data may serve three purposes in MoCAs: as the basis for assessing stress in the *stress modeling* component and determining the situational stressors and the context in the *coping selector*.

Additionally, the MoCA should collect individual characteristics (e.g., age, gender) and coping preferences to inform the *coping selector*.

Storage & Pre-processing: The collected raw data is not directly qualified for analysis. It needs to be pre-processed and stored to be accessible for subsequent *stress modeling* and selection of coping recommendations and actions. Here, various aggregations (e.g., over a specific time frame, combining multiple measures) and transformations (e.g., maximum/minimum, deviation from the mean) may help produce a rich feature set. Since the collected data may be highly sensitive (e.g., physiology, location), significant thought should be put into the confidential and secure storage to maintain privacy.

Stress Modeling: Since a MoCA can only deliver useful coping recommendations if it reliably assesses the user's stress, this component lays the foundation for effective coping support. Here, app designers need to decide whether they prefer binary or low-leveled ordinal stress measures or if a more fine-grained scale is beneficial. While model generation may be relatively straightforward when stress assessment is based on a single or few sensors, complexity rises for systems using a large number of sensors. In all cases, it is recommendable to personalize the model as stress perception is highly individual.

Coping Selector: The *coping selector* analyzes sensor data to identify potential stressors and determines appropriate coping recommendations and actions. The algorithm is described in the subsequent subsection.

Action Processor: This component is responsible for executing the technological actions targeting to prevent stressful situations for the user. Depending on the scope of action to be implemented, interfaces to the operating system (e.g., turn off notifications), other apps on the same mobile device (e.g., re-route messages), or larger multi-platform ecosystems connecting other systems and devices (e.g., inhibit calls on the stationary phone) may be required.

User Feedback: This component delivers stress feedback and coping recommendations to the user. In designing this, two considerations need to be made: when should the app intervene, and how should the intervention be designed? Regarding the *when*, Smyth and Heron (2016) demonstrated that just-in-time stress management interventions are advantageous over feedback only at fixed times. However, Sarker et al. (2017) recommend a short delay to prevent further interruption in high-stress cases. Regarding the *how*, considerations involve the provided functionality and their presentation. Payne et al. (2016) emphasize that effective coping apps should incorporate predisposing (providing general information or knowledge), enabling (available when needed), and reinforcing (rewarding use or progress) elements to accomplish a sustainable behavior change. Schmidt-Kraepelin et al. (2019) recommend developers of behavior change support systems to use gamification to motivate individuals to use the app more regularly and enable healthy behavior changes. Christmann et al. (2018) also suggest a list of techniques to realize behavior change through a stress management app, including gamification elements such as (virtual) rewards (e.g., points, levels, badges) or social comparisons (e.g., leaderboards). As the use of gamification further adds to the fulfillment of the human psychological needs (competence, relatedness, and autonomy) (Schwarzer 2008), similar to the coping strategies themselves, we suggest implementing gamification elements to foster long-lasting behavior changes enabled through needs fulfillment. The presentation of the feedback should factor in that the recipients are likely stressed. Audible push notifications may be inappropriate as they may interrupt and further contribute to stress. Hence, the presentation of feedback should be based on the individuals' preferences and therefore adjustable and changeable.

Evaluation Unit: To evaluate the effect of the coping recommendations, the architecture includes a feedback mechanism that monitors the stress level after the coping recommendation to determine its effectiveness. This component may also be used to refine the stress assessment if the user indicates that they are currently not stressed when presented with the coping recommendations, for example, using active learning (Settles 2010).

Coping Selector Algorithm

To advance the MoCA prototype, we design an algorithm for selecting appropriate coping recommendations and actions in the *coping selector* (Figure 20). This algorithm undergoes three activities to reach MoCA stages 2 (stress understanding), 3 (coping recommendation), and 4 (automated coping support).

The algorithm starts with the *coping selector* receiving a signal from *stress modeling* that elevated stress has been detected. At stage 1, this information can be directly used to provide stress feedback based on this information to the user. To reach stage 2, the algorithm performs additional steps to understand better why the individual is stressed. Therefore, it evaluates the collected sensor data to identify relevant stressors potentially responsible for elevated stress.

Now the algorithm has completed the analytical process that delivers a more detailed understanding of the stressors in the specific situation (stage 2). To reach stage 3, the algorithm further analyzes the individual's context concerning other coping-relevant factors (e.g., time of day, location) and filters potential coping strategies based on the context (*coping recommendations*). This selection is based on information on the individual, sensor data, and a pool of coping strategies and then presented to the user through the *user feedback* component. To reach stage 4, the algorithm selects technological actions that fit the context and lie within the user-defined scope of action to prevent further increase of stress. Finally, the *action processor* executes these actions.

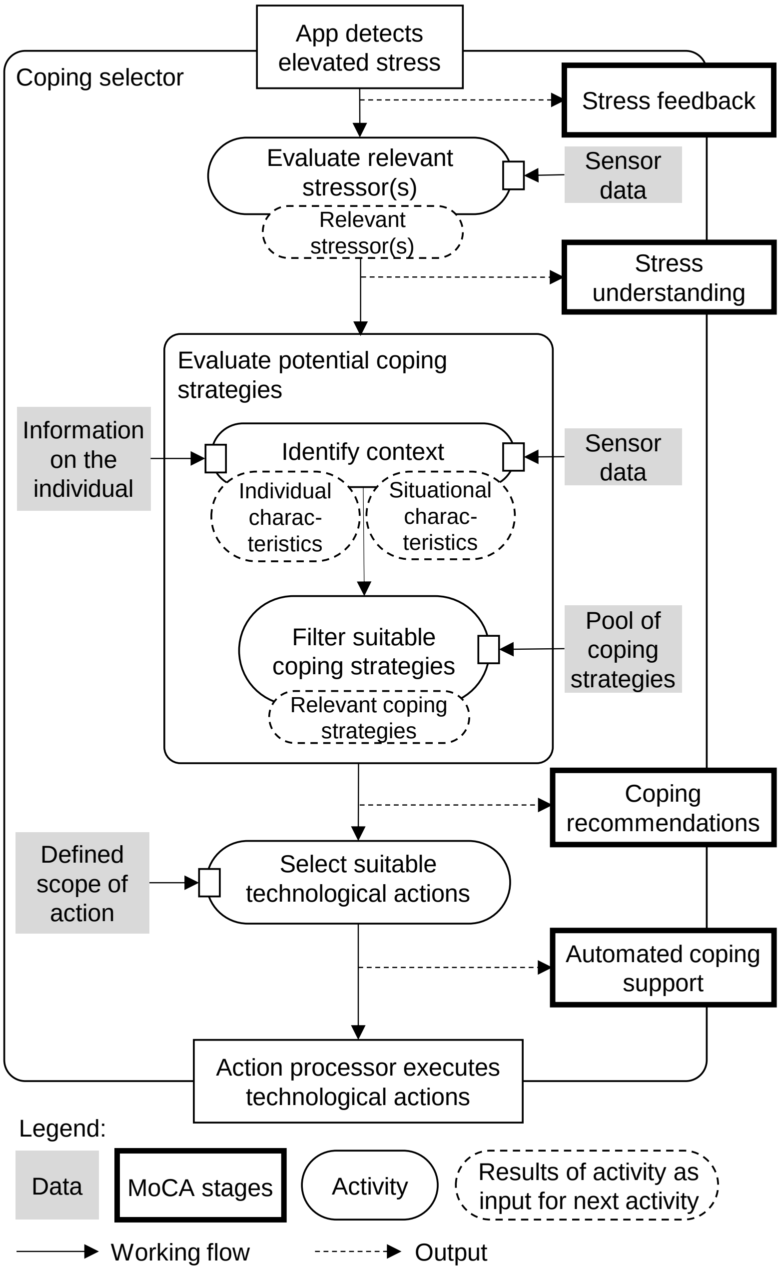


Figure 20: Coping Selector Algorithm

To demonstrate the algorithm, we step through it using an illustrative use case scenario: Ms. Brown works for a mid-sized company as a project manager. It's Thursday, her GPS data points to her work location, the weather is nice, the sun is shining, and her calendar is full of tasks and appointments and leaves room for only a few short breaks. Over the day, she has received many push notifications on her smartphone from different apps. MoCA detects an elevated stress level and triggers the *coping selector*. In a first step, the algorithm evaluates potential stressors based on the sensor data, for example, by searching for unusually high or low values. In our example, this step indicates high values in the ambient sound and notification sensors. It infers that environmental *noise* and *frequent interruptions* may potentially stress the user. The next step aims to collect additional information on the individual's context. Here, the algorithm finds that the GPS sensor points to the workplace and the calendar indicates that Ms. Brown is very busy all day long. From data initially provided by her, the algorithm knows for which meetings she needs to be in front of her laptop and for which meetings a telephone call is sufficient. She also allows the MoCA to turn off notifications. Based on this contextual information, the algorithm filters coping strategies and actions that may apply in this situation and context. Due to the work environment, strategies such as exercising or sleeping may be inappropriate. However, between her current and her next meeting, she may be free to change her location within the office building or take a walk outside in the sun while participating in the next meeting via telephone conference. Based on this inference, the algorithm recommends Ms. Brown to relocate to a quiet environment or go outside for a walk (coping family *escape*) and automatically turns off the notifications (coping family *problem-solving*).

Prototype

To demonstrate the design, we prototypically implemented the MoCA architecture. In its current version, the app senses various behavioral and environmental measures, assesses and reports the user's stress, and delivers insights into potential stressors (stage 2). Stress assessment grounds on an unpersonalized model trained and evaluated in (Gimpel et al. 2019b). In an initial calibration phase, the model is personalized to the user. The user can access various aggregations and visualizations of the sensor data through the app to inform self-reflection and self-regulation. The current version does not yet provide targeted coping recommendations or execute automated technological actions. Stage 3 will be supported in the next version.

The successful prototyping demonstrates the general feasibility of creating HBCSS for stress coping and substantiate that the proposed design qualifies to produce effective MoCAs.

Interesting insights regarding MoCA implementation could be drawn from the iterative development process and alpha (6 testers) and beta testing (8 testers), revealing, for example, that a too frequent inquiry of smartphone sensors drains the battery substantially and reduces user acceptance. Here, trade-offs between timeliness and usability need to be made (Gimpel et al. 2019a). In addition, personalization of stress modeling proved to increase assessment performance clearly but may decrease perceived ease of use as it typically requires user input. An initial calibration phase and sparse later re-evaluations may be bearable (Gimpel et al. 2019a).

Discussion

This study addresses the rising health issue of human stress by proposing an HBCSS design to support individuals cope with increasing stress in work and private life, which we refer to as a MoCA. This design consists of a general architecture including good practices on designing the architectural components and an algorithm describing how a MoCA can use the collected data to report stress feedback (stage 1), determine details on the stressful situation (stage 2), derive appropriate coping recommendations (stage 3), and execute technological actions to prevent stressful situations (stage 4).

The design elements presented here were built and evaluated iteratively following Sonnenberg and vom Brocke (2012). The proposed design fulfills the design requirements by evaluating a continuous stream of sensor data for stress assessment (DR1), facilitating timely intervention in the case of elevated stress (DR2), motivating users towards sustainable behavior changes, for example, by integrating gamification elements (DR3), determining potential stressors, symptoms, and context based on multimodal data (DR4), delivering targeted coping actions and recommendations (DR5), and executing targeted technological stress-preventing actions (DR6). While we do not claim that our solution is the only way how MoCA can be designed, prototyping suggests that the presented design produces effective MoCA.

Our research contributes to the literature in various ways. First, it introduces the concept of an HBCSS aiming to support individuals in coping with daily stress using multimodal sensor data. It envisions an advanced approach to support individuals' stress coping that goes beyond current research, focusing either on the provision of feedback on the user's stress level (Gimpel et al. 2019a) or on the support of coping activities without contextual knowledge of the user's stress perception and user-specific background information (Coulon et al. 2016). Second, we condense existing literature on various streams of mobile coping support and indicate challenges and directions for further research. Third, we present a general design for creating effective MoCAs using knowledge created from analyzing the literature. This design reflects good practices on how to design MoCAs from various research streams, as well as an algorithm for selecting coping recommendations and actions based on the context.

Several practical implications arise from our study. Individuals benefit from a productive MoCA by experiencing fewer stress-related symptoms in their everyday lives. Further, institutions like health insurance companies or organizations whose business model aims at health promotion are concerned about mental health issues. Health insurances, for example, can offer programs around MoCAs to promote healthy behavior. Employers can introduce MoCA to improve their employees' health and productivity.

Naturally, our research is subject to limitations that require further research. First, the prototypical instantiation delivers contextually informed just-in-time stress feedback to the user (stage 2) but does not yet provide targeted coping recommendations (stage 3) or trigger technological actions targeting the prevention of further stress (stage 4). Hence, despite the theory-driven design and first evidence from related work, a real-world evaluation of the effectiveness of coping recommendations to initiate a behavior change is yet up to future research. Second, the pool of coping recommendations has not yet been designed and tested in real-world field studies. In a subsequent study, we plan to investigate what coping strategies and recommendations are helpful in what situations. Third, future research should examine which gamification elements are best to motivate behavior change in the field of stress based on individual characteristics and preferences.

Conclusion

Due to the rising severity of stress for individuals in work and private life, various scholars have constructed and promoted the vision of HBCSS effectively supporting their users in reducing stress by preventing stressful events and facilitating effective coping behavior. Most approaches aim to raise stress awareness and transmit knowledge on stress coping. While these approaches have proven effective, they do not yet explore the full potential of mobile coping support. Our design science research approach explored the question of how to design HBCSS that assist their users in coping with stress using multimodal sensor, individual, and context data to enable a sustainable behavior change in dealing with stress. As the efficacy of coping strategies depends on individuals' characteristics and context, our proposed MoCA design exploits the sensing capabilities of mobile devices to analyze the user's current situation to provide and execute individualized, targeted, automated coping support. We encourage researchers and practitioners alike to intensify the development of MoCA to tackle the rising problem of increased stress for individuals and society and hope to make a small contribution to the ongoing research efforts to eliminate the rising threat of stress.

6. General Discussion and Conclusion

6.1. Summary of Results and Meta-Inferences

Pursuing the objective to support individuals in adopting a healthy DTM use behavior, the research presented here explored various facets of the digitalization of individuals (Matt et al. 2019). Specifically, it examined how individuals behave when using DTM (section 3.1), how their behavior can be influenced (section 3.2), how they can mitigate the consequences arising from their DTM use (Chapter 4), and how mobile stress assessment systems (sections 5.1 and 5.2) and mobile coping assistants (section 5.3) should be designed. Altogether, the individual research activities converge towards an understanding of what aspects are important to design an information system aiming for a sustainable change of behavior, specifically regarding coping with stress. To obtain a multi-faceted view, the dissertation combined a behavioral science and a design science perspective and employed a diverse range of research methods.

Chapter 3 presented insights into individuals' behavior. In the case of a knowledge-intense organization, it found that users at the digital workplace can take eight different roles depending on their communication and collaboration patterns (section 3.1). The roles differ in terms of the use intensity of various functions of the digital workplace suite. Which role a user takes can be partially explained by their hierarchical position within the organization and the length of employment in the organization. Qualitative interviews provide rationales for some of the role-takings and indicate further contributing aspects. In these interviews, users describe that, for example, employees in higher hierarchical positions have comparably little shares of collaboration but are among those who communicate the most because their main responsibility is to lead their subordinates and coordinate with other managers. In contrast, full-time employees without a lead position are the most intensive users of the suite's collaboration features because their task involves the collaborative creation of knowledge and content. The qualitative insights from the interviews suggest that users' behavior is not static but may change over time when the hierarchical position or tasks change.

Adding to this, section 3.2 examined a promising way to change individuals' behavior. A field experiment explored if the provision of real-time feedback on the indoor environmental quality has the potential to change individuals' ventilation behavior at the workplace. The results indicate that ten of eleven participants that received the feedback changed their ventilation behavior resulting in an overall improvement of indoor environmental quality in their offices.

However, the evaluation also suggests that the feedback's effectiveness reduced over time with a slightly but continually decreasing indoor environmental quality during the two-week experimental phase. These findings indicate that behavior change techniques aiming for a sustainable behavior should not only be thoroughly designed but also include reinforcements, for example, by means of gamification elements or varying visualizations.

Chapter 4 revealed insights into individuals' ways to mitigate digital stress as a severe individual consequence of digitalization. The research activity employed a mixed-methods approach combining qualitative and quantitative elements and identified 30 coping responses that adolescents activate to cope with digital stress. The activation of these coping responses differs between adolescents of different grade at school, gender, and the number of technological devices in their possession as a proxy for their technological proficiency. Quantitative analysis revealed five factors indicating behavioral patterns that may determine their selection of coping responses. These findings provide valuable insights regarding potential coping strategies as well as individual and situational characteristics determining the selection of adequate coping strategies.

Complementary, Chapter 5 took a design perspective aiming to mitigate individuals' experiences of stress. Section 5.1 presented a prototype that assesses the user's stress level based on smartphone sensor data. Other than previous research approaches, the prototype aims for a life-integrated assessment of stress which does not obtrude the user or interfere with their habits. Therefore, using elastic net regression, a general model has been created that relates the collected sensor data to individuals' self-reported perception of stress. The model can explain 42 % of the variance in individuals' stress levels. During prototyping, various valuable insights have been drawn that might be informative for other designers of mobile stress assessment systems.

Building on the insights from the development of this prototype and four other prototypes as well as existing literature on the topic, section 5.2 delivered a design theory comprising generalized design knowledge on mobile stress assessment. This knowledge consists of common design requirements, an architectural blueprint, instructive design principles, and design features, as well as a description of various trade-offs that may be necessary during the design of a mobile stress assessment system. Additionally, four archetypes of existing mobile stress assessment systems are presented. This knowledge may help designers of mobile stress assessment systems to build effective stress assessment components. A possible use case of stress assessment is the development of a coping assistant which provides real-time suggestions of adequate coping strategies.

Section 5.3 presented an abstract design of such a system, including an architectural blueprint (building on the blueprint presented in section 5.2) and an algorithm for selecting the coping strategies based on individual characteristics and preferences, situational factors relating to the stressful situation, and contextual or environmental characteristics influencing what coping strategies are possible. The proposed mobile coping assistant constitutes a health behavior change support system that may assist individuals in effectively coping with stress.

The following subsections describe first how the research activities in this dissertation contribute to the IS knowledge bases introduced in section 2.4 and then what practical implications arise from the results of this research.

Theoretical Contributions

Altogether, the research activities presented in this dissertation extend the IS knowledge bases (Ω knowledge, λ design theory, and λ design entities) by delivering descriptive knowledge on individuals' use of DTM as well as prescriptive knowledge on the design of DTM for individuals' use. Thereby, they take on all six modes. The analysis of user roles at the digital workplace (section 3.1) uses extant knowledge on individuals' DTM use behavior (mode 1) to inform the derivation of new, empirically grounded descriptive knowledge on what roles individuals take on in practice (mode 2). The examination of real-time feedback's effectiveness to induce a behavior change (section 3.2) builds on nudging theory (mode 1) and design guidelines for digital nudges (mode 5) to develop a prototype that provides real-time feedback (mode 6) and to understand individuals' responses to this feedback as a behavior change technique (mode 2). The investigation of adolescents' coping behavior as a response to digital stress (Chapter 4) is grounded on theoretical foundations on individuals' DTM use, digital stress, and coping (mode 1; e.g., individuals' DTM use behavior from section 3.1) and delivers new insights related to adolescents' activation of coping responses (mode 2). The mobile stress assessment prototype presented in section 5.1 draws from descriptive knowledge on individuals' experience of stress (mode 1) and delivers a mobile stress assessment instantiation to the design entity knowledge base (mode 6). Building on that, the design theory for mobile stress assessment from section 5.2 is additionally informed by a multitude of design entities (mode 5; e.g., the prototype from section 5.1) and dispersed design knowledge (mode 3; e.g., the insight that real-time feedback works from section 3.2) to deliver a generalized design theory (mode 4). The design of a mobile coping assistant (section 5.3) builds on stress and coping knowledge (mode 1; e.g., adolescents' coping responses from Chapter 4) as well as design entity (mode 3; e.g., the instantiation of real-time feedback from section 3.2) and design theory knowledge (modes 3 and 5; e.g., the mobile stress assessment design theory from section 5.2) to create abstract prescriptive knowledge how to design such a solution (mode 4). In the following, the research activities' contributions to each of the three knowledge bases are described in more detail.

First, various elements of the research in this dissertation deliver descriptive knowledge on individuals' DTM use extending the Ω knowledge base. Thereby, sections 3.1 and 3.2 focus on behavioral aspects of individuals' DTM use (Matt et al. 2019). Complementary, Chapter 4 examines ways how individuals can mitigate the consequences of DTM.

The user roles elaborated in section 3.1 advance our understanding of individual differences in communication and collaboration behavior at the digital workplace. As one of few studies building the analysis on real-world interactional data, it provides empirical evidence for the presence and the characteristics of different user roles at the digital workplace. Partially, the identified user roles substantiate the relevance of previously described roles that users may take at the digital workplace (e.g., Alavi and Leidner 2001; Reinhardt et al. 2011; Schlagwein and Hu 2017; Wang and Noe 2010). In addition, other roles which have already been described for non-work-related contexts (Arazy et al. 2016) seem to transfer to the digital workplace, indicating that individual characteristics contribute to determining the behavior. However, quantitative and qualitative analysis of covariates of individuals' behaviors further suggests that hierarchical or task-related aspects also play in. The finding that top-level managers use the communication features of the digital workplace suite more often than the collaboration features supports a proposition of the organizational knowledge creation theory stating that individuals in higher hierarchical positions are not the primary creators of knowledge but rather those who communicate visions about knowledge throughout the organization (Nonaka et al. 2006). Overall, the results from section 3.1 extend the descriptive knowledge on individuals' behavior at the digital workplace. Future research can build on the results from section 3.1 by examining further covariates of interaction behavior and evaluating if an individual changes their role over time and what triggers may be influencing this change.

The experimental modification of individuals' office ventilation behavior using real-time feedback in section 3.2 creates new descriptive knowledge on the effectiveness of automated feedback as a behavior change technique. Overall, real-time feedback on the office's indoor environmental quality seems to be an effective and promising way to induce a change of ventilation behavior. This conclusion is in line with studies using a similar nudge to induce a behavior change in other contexts (e.g., Tiefenbeck et al. 2013; Tiefenbeck et al. 2019). Yet, the results also suggest that the feedback did not reach all participants equally, with some participants stating that they perceived the feedback as distracting or that they have not changed their behavior in response to the feedback. Also, the feedback's effect reduced over time for most participants. This may be explained by a habituation effect (Hollands et al. 2016). The indoor environmental quality feedback may have first created a phase of excitement in which individuals reacted consciously to the feedback, followed by a phase of habituation in which the individual's awareness of the presence of both the feedback and the own behavior decreased. Yet, to reach a sustainable behavior change, the behavior needs to be internalized to the extent that the individual performs it automatically and subconsciously (Louis and Sutton 1991). Future research can expand the collected knowledge on the effectiveness of real-time feedback by exploring how the target behavior can be reinforced to reach a sustainable change of behavior (Elder et al. 1999). Additionally, the experimental setting could be transferred to other contexts (e.g., stress coping) and explore how the feedback should be designed (e.g., in terms of visual presentation and auditive or haptic signals) for best-possible behavior change effects.

Chapter 4 delivers descriptive knowledge on adolescents' ways of coping with digital stress. Although previous research has examined digital stress coping from a high-level perspective (e.g., Beaudry and Pinsonneault 2005; Galluch et al. 2015; Salo et al. 2017) or at the example of only a few digital stressors (e.g., Li et al. 2019; Weinstein et al. 2016), the integrated approach considering a large variety of digital stressors and the focus on adolescents taken in this dissertation are new to the digital stress coping literature. As a result, the list of 30 coping responses is currently the most comprehensive list of actionable strategies qualified to mitigate digital stress. It goes beyond existing knowledge of how adolescents cope with stress in general (de Anda et al. 2000; Hampel et al. 2018; Zimmer-Gembeck and Skinner 2011) because it provides specific recommendations for the elimination and emotional handling of digital stressors. In addition, the results of the quantitative analysis provide first insights into covariates of individuals' coping behavior, revealing that girls tend to use more avoidant coping responses, coping behavior becomes more self-determined in higher grades, and that some coping responses act universally whereas others are specific to single digital stressors. Parts of these insights, for example, the finding that girls tend to avoidant coping (Ptacek et al. 1994), are congruent with previous literature. Exploratory factor analysis indicates that adolescents' coping behavior may be determined by five factors, named *Avoid Stressful ICT, Follow the Rules*, *Use ICT Consciously*, *Contain Negative Emotions,* and *Acquire ICT*. Future research can extend the results by contrasting digital stress coping in adolescent and adult populations, analyzing further covariates of coping behavior, and diving deeper into the factorial structure of coping behavior. The knowledge created in Chapter 4 may also be informative to the design of information systems aiming to support individuals in coping with stress.

Second, besides descriptive knowledge, the dissertation at hand also comprises prescriptive knowledge contributing to the λ knowledge base. Thereby, the research in sections 5.2 and 5.3 produced generalized prescriptive knowledge extending the design theory knowledge in the λ knowledge base.

Building on 136 mobile stress assessment studies and five own prototyping activities, section 5.2 elaborates generalized prescriptive knowledge on the design of mobile stress assessment systems. This knowledge is presented in the form of a design theory comprising all relevant components proposed by Gregor and Jones (2007). The design theory consists of multiple elements (design requirements, architectural blueprint, design principles, design features, and trade-offs), which are instructive to both the design process and the implementation of mobile stress assessment systems (vom Brocke et al. 2020b). Being the outcome of a series of research efforts on various aspects of mobile stress assessment, the design theory has been evaluated in terms of a multitude of quality criteria, including its generality, utility, and effectiveness (Sonnenberg and vom Brocke 2012). Thus, it constitutes a mid-range design theory, including mature and complete design knowledge (Gregor and Hevner 2013). The design theory can serve other researchers as an example of a comprehensive design theory that might inspire them to elaborate and present their design theory in a similar way. More importantly, the prescriptive knowledge contained in the design theory can help researchers to instantiate mobile stress assessment as an elementary data source for more sophisticated workflow or assistance systems such as stress-sensitive adaptive enterprise systems (Adam et al. 2017) or mobile coping assistants.

Section 5.3 expands further on the idea of a mobile coping assistant and delivers an abstract design proposal for such systems. Conceptualized as a type of health behavior change support system, the mobile coping assistant aims to persuade individuals to take appropriate actions to successfully cope with stress. Against this background, the proposed design suggests four implementation stages employing additive strategies to achieve a sustainable behavior change (Oinas-Kukkonen and Harjumaa 2009). These stages range from the mere provision of real-time stress feedback to the automatic execution of technological actions supporting individuals' coping efforts. To facilitate the development of mobile coping assistants, the section delivered prescriptive knowledge in the form of an architectural blueprint, reasoned starting points for designing the architectural components, and an abstract algorithm for selecting adequate coping recommendations. While the knowledge presented in this section does not yet constitute a design theory and is thus less mature than the design theory from section 5.2, it contains abstract prescriptive knowledge on how to design a mobile coping assistant that needs yet to be evaluated in practice. Further research should expand on this by instantiating the proposed design and testing its applicability and utility in artificial as well as in real-world settings.

Lastly, in the course of this dissertation, various artifacts have been created that add to the λ design entity knowledge base. The test of real-time feedback as a means to induce a behavioral change in section 3.2 has produced a prototype of a sensor-based feedback system. This prototype constitutes an artifact or design entity that may be informative for the design of similar feedback systems. In addition, five mobile stress assessment prototypes have been presented in sections 5.1 and 5.2. These instantiations also add to the design entity knowledge on mobile stress assessment that future researchers can build upon.

Practical Implications

Various practical implications arise from the research in this dissertation. Practitioners can benefit from the dissertation mainly in three ways:

First, the knowledge presented in Chapter 4 and sections 3.1, 3.2, and 5.3 can help individuals become aware of their DTM use, the downsides of their DTM use (in particular, digital stress), and ways to address these downsides. Information on their own DTM use behavior, for example, in the form of user roles (section 3.1), may set them reflecting about their DTM use and encourage a conscious use of DTM, which has been found to be a promising way to reduce digital stress (Chapter 4). In general, knowledge on coping responses targeting digital stress

(Chapter 4) allows individuals to improve their coping skills, draw from a broader portfolio of coping responses, and select adequate coping responses when confronted with stress. To sustain effective coping behavior, individuals may voluntarily revert to persuasive elements such as real-time feedback (section 3.2) or smart assistance systems (section 5.3).

Second, a better understanding of the behavior and consequences associated with individuals' DTM use may help different social contexts (e.g., organizations, schools, families) shape an environment in which individuals' psychological needs can be better addressed, potentially reducing their exposure to stressful encounters. Here, especially the results of Chapters 3 and 4 play in. Interindividual differences in DTM use behavior (section 3.1) suggest that different individuals may need to be addressed differently. Social contexts such as organizations can use this knowledge to harness and foster individuals' strengths and provide targeted support or training to address their weaknesses. Thereby, this knowledge can serve both instrumental and humanistic objectives. The provision of feedback (section 3.2) or other nudges may be an effective means to induce a sustainable behavior change. In addition, in cases of joint responsibility, for example, for the indoor environmental quality of offices occupied by two or more people, the enthusiasm of a single person may be contagious for others. The social environment also plays a central role in coping with stress when a stressed individual can rely on instrumental or emotional support from their peers (Chapter 4). In addition, organizations, schools, and families can use the knowledge on the consequences of DTM use and potential countermeasures from Chapter 4 to shape a social and technological environment in which individuals experience fewer stressful events.

Third, the knowledge on the consequences of DTM from Chapter 4 enables DTM designers developing new information systems to consider the demands they put onto their users in advance. With the users' psychological needs in mind, they might, for example, limit the use of notifications or include content filters to prevent depictions of violence for adolescents. In addition, DTM designers can use the design knowledge presented in sections 5.1, 5.2, 5.3, and 3.2 to produce information systems that are sensitive to the user's stress or support them in successfully coping with stress.

6.2. Limitations and Outlook for Future Research

Naturally, the research in this dissertation is subject to limitations and indicates potential for future research. This section gives a summary of the limitations and an outlook for future research.

First, only selected aspects of individuals’ behavior in the digitalized world have been researched. Therefore, the dissertation cannot deliver a comprehensive understanding of how individuals behave due to digitalization. Likewise, the research could only shed light on some behavioral aspects that are relevant to induce a behavior change, questioning if the design of a mobile coping assistant building upon these behavioral foundations is the right approach for all individuals. Further limitations arise from the two research studies in Chapter 3 dealing with the individuals’ behavior.

In section 3.1, the data set used to derive the user roles stems from a single organization. Other knowledge workers in other organizations using the same digital workplace suite may show different usage patterns. Similarly, parts of the effect may be due to the choice of the digital workplace suite and other digital workplace suites might be used differently. Therefore, future research should explore user roles based on real-world data of other organizations using the same or other digital workplace suites. Since data is only available for the digital parts of communication and collaboration, non-digital parts could not be considered in the user roles, although they might make up an important share of interaction among less technology-savvy knowledge workers. In addition, for privacy reasons, the analysis considered only the number of interactions but not their content. Therefore, no conclusions can be drawn on the effort an individual puts into a single interaction. Thus, more knowledge-intense interactions may be underrepresented in the user roles. The clustering of users based on the interactional data follows an explorative approach in which the composition and interpretation of the roles are looked at jointly. Future research should investigate if they can confirm the compilation of these user roles. Additionally, the study examined only a single data set comprising three months of interactional data. Future research should analyze to what extent the roles assigned to individual users change over time, for example, as a result of changing individual preferences, altered tasks, or other external triggers.

In section 3.2, the experiment analyzed the effectiveness of real-time feedback in the field. To prevent disruptions of the employees’ workflow and productivity, not all potentially confounding variables could be controlled. In addition, it seemed that not all participants reacted equally to the real-time feedback. The data suggests that in some offices, the air quality did not improve after the start of the treatment, whereas it improved heavily in other offices. An analysis of the determinants of individuals' reactions to the nudge is up to future research. Further, after a stark improvement of the indoor environmental quality at the beginning of the treatment, it declines after the initial peak. Although this is consistent with other studies and typically explained with the setting in of a habituation effect, future research should further explore potential reasons for this and ways to reinforce or sustain the effect.

Second, with its focus on digital stress, the dissertation provides only an incomplete view of digitalization's consequences on individuals. But the study of digital stress is also subject to some limitations. Since it targeted mainly adolescents, it is not clear if and to what extent the suggested coping responses transfer to adults' experience of digital stress. Several decisions regarding the research design further limit the results. To maintain the adolescents' privacy and create a space in which they can speak freely, the workshops were not taped and transcribed, reducing the number of qualitative insights that could be drawn from them. The questions in the workshops were formulated in a way that they left the adolescents room to mention hypothetical digital stress events or coping responses. A small part of the adolescents took part in both the workshops and the quantitative survey. It cannot be excluded that the prior participation in the workshops might have biased their answers to the survey. The results of younger adolescents (specifically, grades 5 and 6) are difficult to interpret because fewer adolescents took part in the quantitative survey and those that did seemed to be less reflected about their DTM use than older groups. Besides addressing this age-related issue, future research should confirm the identified associations with further covariates of adolescents' activation of coping responses such as gender or technological proficiency.

Third, the design of new information systems for individuals leaves room for extension. The prototype for life-integrated stress assessment in section 5.1 is only one instantiation of mobile stress assessment for a specific purpose. For the prototype to work reliably, it is, for example, a requirement that the individual uses a single device for both work and private purposes. Otherwise, the data basis would not be able to fully grasp all factors that contribute to the individual's stress experience. Additionally, it relates the sensor data to perceived stress which is not necessarily identical to biological stress. Future research should test the model derived from the prototype with a larger population and a longer period of time. In addition, further ways should be explored to improve the model and make it more robust. As one means, a prototype introduced in section 5.2 builds on the model and creates personalized models for single users. Section 5.3 reuses components of the prototype to provide coping support to the user. In the future, mobile stress assessment may be the foundation for other smart assistance systems such as stress-sensitive adaptive enterprise systems (Adam et al. 2017).

In section 5.2, the design theory on mobile stress assessment builds on an extensive amount of MSA studies. Yet, the literature search did not include research in all disciplines, outlets, and publication years. Not considered studies might add informative facets to the design that were not considered in the design theory. The own prototyping activities informing the design theory do not cover the full spectrum of mobile stress assessment systems. Therefore, at some parts, the design theory needs to rely on theoretical knowledge explicitly or implicitly mentioned in the literature. Further prototyping activities may deliver further insights into the opportunities and challenges of MSA system design.

The prototype in section 5.3 does not yet comprise the full functionality of a mobile coping assistant and needs to be extended to cover stages 3 (coping recommendations) and 4 (automated technological actions). Likewise, the design needs to be further evaluated in a real-world application in the context of Eval 4 in the evaluation framework of Sonnenberg and vom Brocke (2012). In addition, further research is required on the specific design of stage 3 or stage 4 mobile coping assistants. This includes the development and testing of a comprehensive set of coping recommendations and actions as well as a theoretically grounded strategy to persuade individuals towards a behavior change (Oinas-Kukkonen and Harjumaa 2009).

6.3. Conclusion

The research presented in this dissertation contributes newly created knowledge to various highly topical IS research streams. It takes both a descriptive and constructive approach to analyze and design individual information systems with the goal of facilitating a behavior change, specifically regarding individuals' coping with stress. Thereby, it combines three interrelating perspectives on the digitalization of the individual: the individual's behavior, consequences that DTM have on them, and the design of future DTMs (Matt et al. 2019). The insights gained from these perspectives advance the understanding of individuals' DTM use at the workplace (section 3.1), the effectiveness of feedback to induce a behavior change (section 3.2), adolescents' ways to cope with digital stress (Chapter 4), the design of systems that assess stress based on mobile sensor data (sections 5.1 and 5.2), and, ultimately, the design of a mobile coping assistant that aims to support individuals in improving their stress coping behavior.

Altogether, these insights aim to contribute to the creation of a digitalized world in which DTM are less stressful, less threatening, and less harmful to individuals' health than today. However, there is still a long way to go. Therefore, substantial research efforts are required to understand the full bandwidth of behaviors, consequences, and design opportunities associated with individuals' digitalized world. As a society, we should leave nothing undone to prevent that the ongoing digitalization of everything leaves people behind or does damage to them. Only then will we be able to shape a socio-technical environment that creates more benefit than harm for all individuals.

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Appendix A – How DTM Users React to Real-Time Feedback

Appendix A.1 – Average IEQ in Control and Treatment Groups over Time

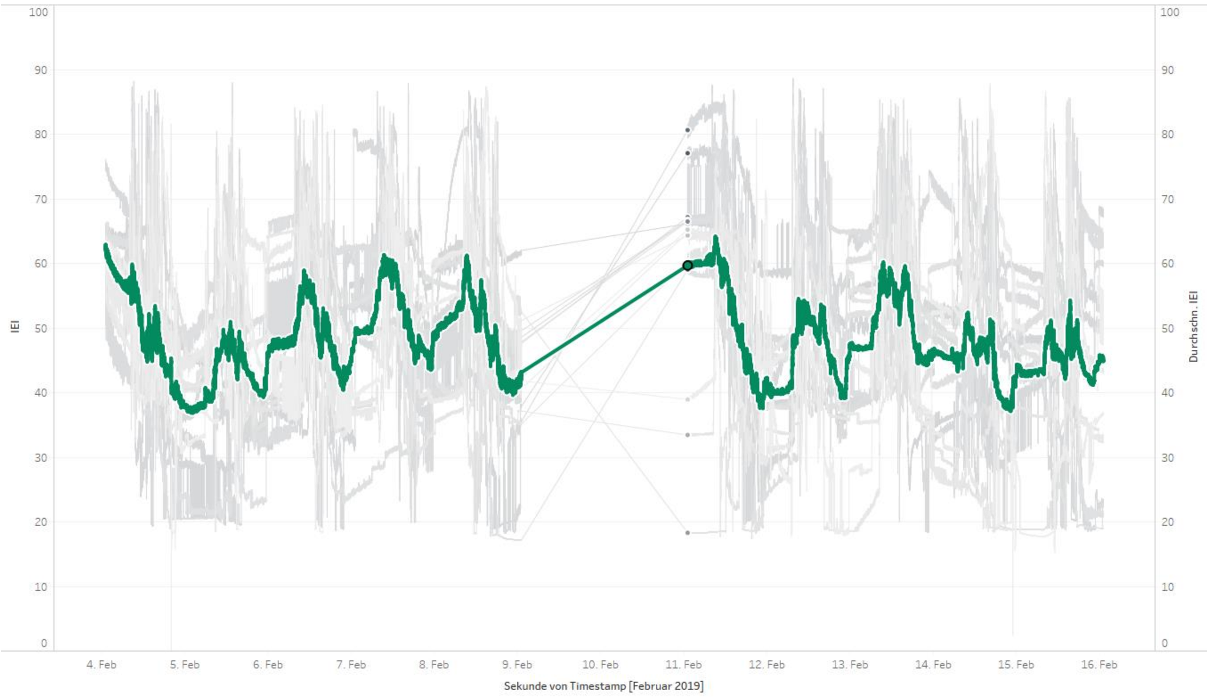

Figure 21: Average IEQ of All Participants (Control and Treatment Groups) in the Baseline Phase

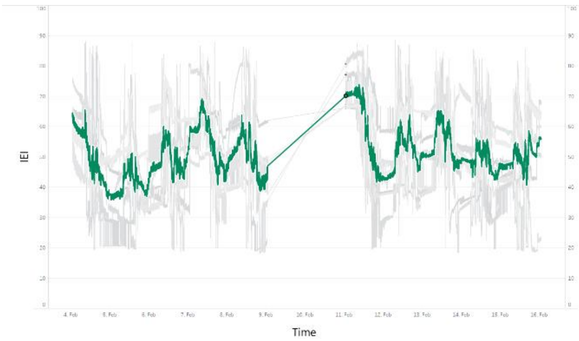

Figure 22: Average IEQ of Control Group in the Baseline Phase

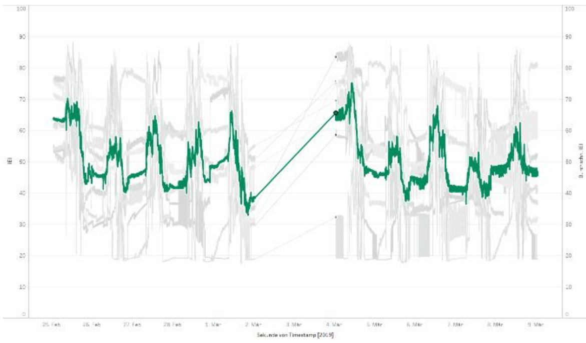

Figure 23: Average IEQ of Control Group in the Treatment Phase

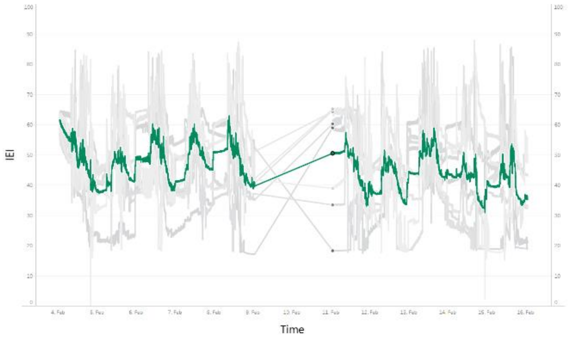

Figure 24: Average IEQ of Treatment Group in the Baseline Phase

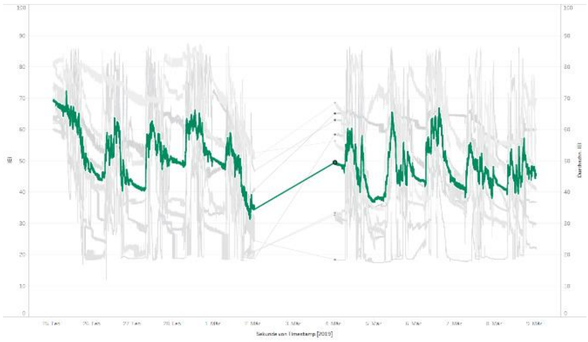

Figure 25: Average IEQ of Treatment Group in the Treatment Phase

Appendix B – Analyzing Individuals' Responses to Consequences of Their DTM Use

Appendix B.1 – Scales & Scale Evaluation

This appendix provides details on the scales used within the technostress creator questionnaire (Table 25) as well as their evaluation (subsequent text). Table 14 in the main text of the paper gives an overview of the coping responses in the coping questionnaire. Since we assess the activation frequency of these coping responses based on single items for each individual coping response, this part of the survey is evaluated within the analyses of Study 2.

Scales (items were translated to German for the survey)	Origin
Overload	
OV1: I feel pressured due to ICTs.	Ayyagari et al. 2011
OV2: I feel that I receive too many messages and too much information via ICT.	Maier et al. 2012; Tarafdar et al. 2007
OV3: I'm bothered that I too often deal with my friends' problems due to ICT.	Maier et al. 2012
OV4: I feel pressured because other people want me to do more through ICT.	Lim and Choi 2017
OV5: I feel pressured to congratulate friends as a consequence of the birthday reminder on social networks.	Maier et al. 2012
Invasion	
IV1: I'm bothered that I can spend less time with my family due to ICT.	Tarafdar et al. 2007
IV2: I perceive that I have to sacrifice my leisure time to keep current on new ICT.	Tarafdar et al. 2007
IV3: It bothers me to receive too much advertising through ICT.	Lim and Choi 2017
IV4: I feel my personal life is being invaded by ICT.	Tarafdar et al. 2007
IV5: I feel that using ICT for school creates conflicts in my personal life.	Ayyagari et al. 2011
Complexity	
CO1: I need a long time to understand and use new ICT.	Maier et al. 2012; Tarafdar et al. 2007
CO2: I often find ICT too complex to use.	
CO3: I do not find enough time to study and upgrade my ICT skills.	
CO4: I do not know enough about ICT to use them effectively.	
Uncertainty	
UC1: I don't like that there are always new developments in ICT.	Tarafdar et al. 2007
UC2: I don't like that there are always new terms and services for ICT.	Maier et al. 2012
UC3: I don't like that there are constant changes to software (e.g., mobile and computer apps) I use.	Tarafdar et al. 2007
UC4: I'm bothered that upcoming updates might influence my future use of ICT negatively.	Tarafdar et al. 2007
UC5: I don't like that there are constant changes with respect to devices and hardware.	Tarafdar et al. 2007
UC6: I don't like that I have to renew my ICT skills to use them.	Tarafdar et al. 2007

Scales (items were translated to German for the survey)	Origin
Insecurity	
IS1: I feel threatened by ICT because I do not know which jobs will be replaced by ICT.	Ayyagari et al. 2011; Tarafdar et al. 2007
IS2: I feel that I have to constantly update my skills with ICT in order to find a job in the future.	Tarafdar et al. 2007
IS3: I feel unsettled because I do not know how ICT change future workplaces.	Ayyagari et al. 2011; Tarafdar et al. 2007
IS4: I believe that I might be replaced more easily due to ICT.	Tarafdar et al. 2007
Unreliability	
UR1: I'm annoyed because ICTs frequently cause problems. UR2: I'm annoyed because ICTs frequently slow down things. UR3: I'm annoyed because I always have to expect technical errors when using ICT. UR4: I'm annoyed because ICTs frequently cannot be relied on.	Items self-developed on the basis of Ayyagari et al. 2011; Fischer and Riedl 2015; Hudiburg 1995
Social Pressure	
SP1: I don't like that people who are important to me (family, friends) expect me to use specific ICT.	Maier et al. 2012; Weinstein and Selman 2016a
SP2: I don't like that people in my wider social environment (classmates, sports clubs) expect me to use specific ICT.	Maier et al. 2012; Weinstein and Selman 2016a
SP3: I feel unsettled when people who are important to me demand access to private accounts or request private photographs.	Weinstein and Selman 2016a
SP4: I feel annoyed that my use of ICT is determined by others (e.g., when and how I should respond to messages).	Maier et al. 2012; Weinstein and Selman 2016a
SP5: I find it difficult to match my own use of ICT with the behavior of my social environment (family, friends, classmates, sports club).	Weinstein and Selman 2016a
Disclosure	
DC1: I feel that my use of ICT makes it easier to invade my privacy.	Ayyagari et al. 2011
DC2: I worry that information stored in ICT may not be safe.	Lim and Choi 2017
DC3: I am concerned about the misuse of my personal information in ICT.	Lim and Choi 2017
DC4: I am insecure about what happens with my personal information when I input them in ICT.	Lim and Choi 2017; Maier et al. 2012
DC5: I feel uncomfortable that my use of ICT can be easily tracked and monitored.	Ayyagari et al. 2011

Table 25: Scales of the Technostress Creators in Study 2

Shapiro-Wilk tests suggest a rejection of the normality assumption for all technostress creators. We use established survey scales where available to achieve content validity. The self-developed scale for *Unreliability* builds on qualitative findings following a process inspired by Bearss et al. (2016). Based on literature discussing the effect of unreliable ICT (Ayyagari et al. 2011; Fischer and Riedl 2015) or computer hassles (Hudiburg 1995), we first derived a construct definition of *Unreliability* (Table 4) for our study before developing the respective scale (Table 25). We used the Computer Runtime Errors subscale of the Computer Hassles Scale (Hudiburg 1995), which gives a good impression of situations in which computers behave unreliably as a starting point for item generation. In in-depth discussions in the research team, we removed items that are already covered by other technostress creators (e.g., *updated software requirements* as an aspect of *Uncertainty*, *poor user/computer interface* as an aspect of *Complexity*) or do not generalize to modern ICT (e.g., *illegal input message*). We found that there are four overarching aspects corresponding to our construct definition: ICT having technical errors (e.g., *computer hardware failure*, *crashed program*, *damaged storage media*), ICT causing problems (e.g., *lost in the computer*, *forgot to save work*), ICT slowing things down (e.g., *slow program speed*, *slow computer speed*), or being not to be relied on (e.g., *lack of computer application software*, *incompatible software program*, *data are lost*). As the initial scale would be too long for our purpose, we constructed one item for each of these overarching aspects and pose that the theoretical elicitation supports content validity. While we did not verify the scale with a pre-test, the following quantitative analysis and validation demonstrate convergent and discriminant validity. To ensure comprehensibility, we reviewed the items' wording first within the research team and then in discussions with one teacher and two adolescents (grades 7 and 11).

To assess the internal consistency of all scales, we use Cronbach's alpha. For most scales, Cronbach's alpha indicates satisfactory internal consistency with alpha values greater than .70 (Table 26). However, the scales for *Overload* (alpha = .64) and *Invasion* (alpha = .55) fail this benchmark.

Technostress creator	Alpha	Internal consistency
Disclosure	.91	Excellent
Unreliability	.78	Acceptable
Invasion	.54	Poor
Uncertainty	.84	Good
Insecurity	.82	Good
Social Press.	.75	Acceptable
Overload	.64	Questionable
Complexity	.83	Good

Table 26: Cronbach's Alpha for the Technostress Creator Scales

We assess discriminant validity via the Fornell-Larcker criterion (Fornell and Larcker 1981). Table 27 shows inter-construct correlations and the square root of the average variance extracted (AVE). The Fornell-Larcker criterion is met for all constructs except *Overload* and *Invasion*, suggesting satisfactory discriminant validity for all other constructs.

	Disclosure	Unreliability	Invasion	Uncertainty	Insecurity	Social Pressure	Overload	Complexity
Disclosure	(.82)							
Unreliability	.47	(.69)						
Invasion	.38	.47	(.44)					
Uncertainty	.55	.53	.44	(.69)				
Insecurity	.51	.39	.35	.40	(.73)			
Soc. Pressure	.44	.45	.46	.51	.45	(.62)		
Overload	.50	.46	.45	.48	.39	.53	(.52)	
Complexity	.29	.41	.35	.38	.29	.32	.21	(.74)

Table 27: Spearman Correlations of the Technostress Creators with Square Root of AVE on the Diagonal

Furthermore, *Invasion* exhibits a high disparity in scores between the items. For example, item *IN.3* (*"I get too much personalized advertising"*) scored highest of all items in the technostress creator questionnaire, while other items of this construct stay significantly behind. Due to the issues with the internal consistency of both *Overload* and *Invasion* and discriminant validity of *Overload*, we drop both constructs from the analyses. Due to the finding that the technostress creators are not normally distributed, we use the MLM estimator – a maximum likelihood estimator with robust standard errors and a robust test statistic suitable in case of non-normality. Common key figures for determining the model quality based on CFA indicate a reasonable model fit (Table 28) based on common thresholds (Hu and Bentler 1999)

			Thresholds	
		Model	Good	Acceptable
Absolute fit	Relative chi-square (X^2/df)	1.713	< 3	< 5
Overall model fit	Root Mean Square Error or Approximation (RMSEA)	0.047	< 0.05	< 0.08
	Standardized Root Mean Square Residual (SRMR)	0.064	< 0.08	-
Incremental fit	Comparative Fit Index (CFI)	0.921	> 0.95	> 0.85
	Tucker-Lewis Index (TLI)	0.913	> 0.95	> 0.8

Table 28: CFA Indicators and Thresholds for the Model of Technostress Creators

Appendix B.2 – Adolescents’ Perception of Technostress

Detailed Results on the Perception of Technostress Creators

Descriptive statistics and analysis of variance

After removing incomplete data (i.e., all responses where more than three items of the technostress creator questionnaire were not answered), 230 complete responses on adolescents’ technostress remain. The analysis of these responses suggests that adolescents perceive only little technostress with an average score of 2.41 across all technostress creators on a scale ranging from 1 to 5, where 1 denotes a low perceived intensity of the technostress creator and 5 denotes a high intensity. At a closer look, however, we find large differences in intensity between the eight technostress creators. While adolescents perceive the highest technostress from *Disclosure* (mean = 3.04), *Complexity* places the lowest demands on adolescents (mean = 1.71. Table 29 displays the descriptive statistics for all constructs. Figure 26 visualizes the reported intensity of technostress for the six technostress creators.

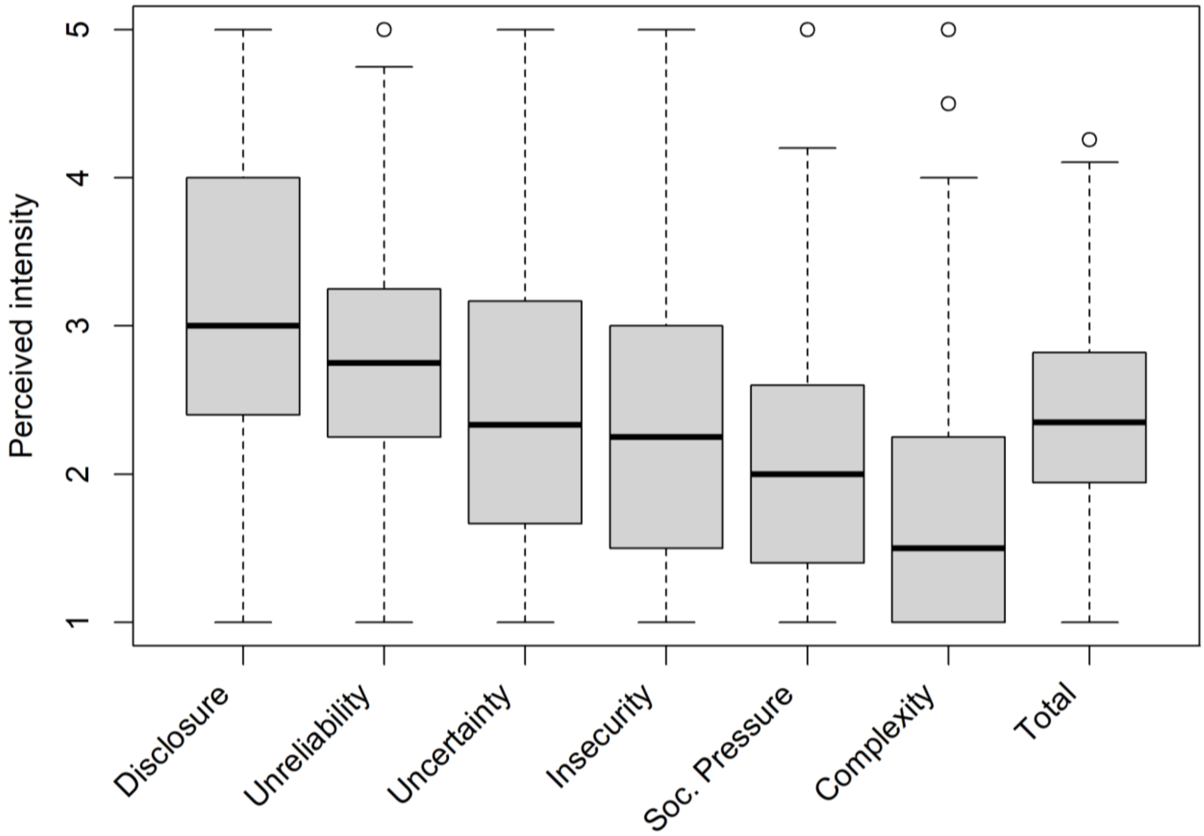

Figure 26: Adolescents’ Perceived Intensity of the Six Technostress Creators (n = 230)

Technostress creator	Mean	Med.	SD	Disclosure	Unreliability	Uncertainty	Insecurity	Soc. Pressure	Complexity
Disclosure	3.04	3.00	1.12	-	-	-	-	-	-
Unreliability	2.77	2.75	0.89		-	-	-	-	-
Uncertainty	2.44	2.33	0.95	***	**	-	-	-	-
Insecurity	2.34	2.25	0.99	***	***		-	-	-
Social Pressure	2.13	2.00	0.89	***	***	**		-	-
Complexity	1.71	1.50	0.77	***	***	***	***	***	-
Total	2.41	2.35	0.68						

Note: Significance codes: *** = p < 0.001, ** = p < 0.01, * = p < 0.05

Table 29: Descriptive Statistics of Technostress Creators and Significant Mean Differences (n = 230)

To further interpret the results, we employ a Kruskal-Wallis test for non-normally distributed data. This test reveals that significant differences in the mean values of the individual technostress creators exist (significance level < 0.01 %). To detect differences in pairs of technostress creators, we additionally perform pairwise Wilcoxon rank sum tests with the Bonferroni p-value adjustment and present the results of this analysis in Table 29. We observe that most of the constructs differ significantly in terms of their means, except for three pairs.

Jointly analyzing the means and mean differences (Table 29), adolescents report the highest intensity of technostress resulting from the group *Disclosure* and *Unreliability*. The technostress creators *Uncertainty, Insecurity,* and *Social Pressure* can be assigned to a second group, which has a lower impact on adolescents' technostress perception. Within those groups, slight deviations may occur due to the insignificances shown. *Complexity*, however, is undeniably the technostress creator that accounts for the least technostress in adolescents. An analysis of the pairwise correlations yields similar correlations to those reported in other technostress studies (Maier et al. 2015b; Tarafdar et al. 2010).

In order to further investigate the connectedness of the technostress creators, we calculate Spearman correlations for all pairs (Table 27) and find that all pairs show moderately positive correlations. The minimum correlation is .21, and the maximum correlation is .55. *Complexity* exhibits the lowest correlations and seems to be easiest to distinguish from the other constructs. While these correlations are rather high, they are similar to those reported in other technostress studies: Tarafdar et al. (2010) report a maximum correlation of .55 and Maier et al. (2015b) a correlation of .50 for the most correlated pair of technostress creators. Since we build on their scales and items for several constructs, these findings are not surprising. Another explanation could be that adolescents might not be so strongly reflected in their perception of technostress and, thus, might have problems locating the exact cause of their technostress.

Relationship of demographic data and technostress creators

We further investigate if the technostress creators show significant associations with demographic data. Table 30 shows the Spearman correlations of grade and of devices with the technostress creators and the point-biserial correlations of gender with the technostress creators.

Technostress creator	Grade^{s}	Devices^{s}	Gender^{b} (overall)	Gender^{b} (subsample)
Disclosure	**.338*****	**-.136***	**.333*****	**.409*****
Unreliability	**.263*****	-.094	**.314*****	**.252****
Uncertainty	**.148***	**-.169***	**.318*****	**.316*****
Insecurity	**.369*****	**-.137***	**.163***	**.175***
Social Pressure	**.140***	-.091	**.311*****	**.310*****
Complexity	.077	**-.245*****	**.189****	**.184***
Total	**.329*****	**-.176****	**.377*****	**.395*****

Notes: Significance codes: *** = p < .001, ** = p < .01, * = p < .05
"Gender (subsample)" reports the results of the robustness check with the urban higher educational secondary school
^{s} Spearman correlations, ^{b} point-biserial correlations

Table 30: Correlations of Technostress Creators with Demographic Data

The correlations indicate that both gender and grade are highly related to the perception of technostress. To better understand these relationships, we perform additional analyses. Wilcoxon-Mann-Whitney tests comparing gender differences for all technostress creators suggest that the difference between girls and boys is significant in all cases and in four of the six cases with high confidence ($p < .001$). While girls reported an average overall intensity of technostress of 2.69, the perceived intensity for boys is only 2.18. For grade, the effect is slightly less pronounced. Kruskal-Wallis tests suggest that significant mean differences exist for all technostress creators except for *Uncertainty*. Although the correlations of *Social Pressure* and grade, as well as of *Complexity* and grade, are weak and insignificant, the Kruskal-Wallis tests unveil significant differences in the means. Figure 27 visualizes adolescents' reported overall intensity of technostress in relationship to grade.

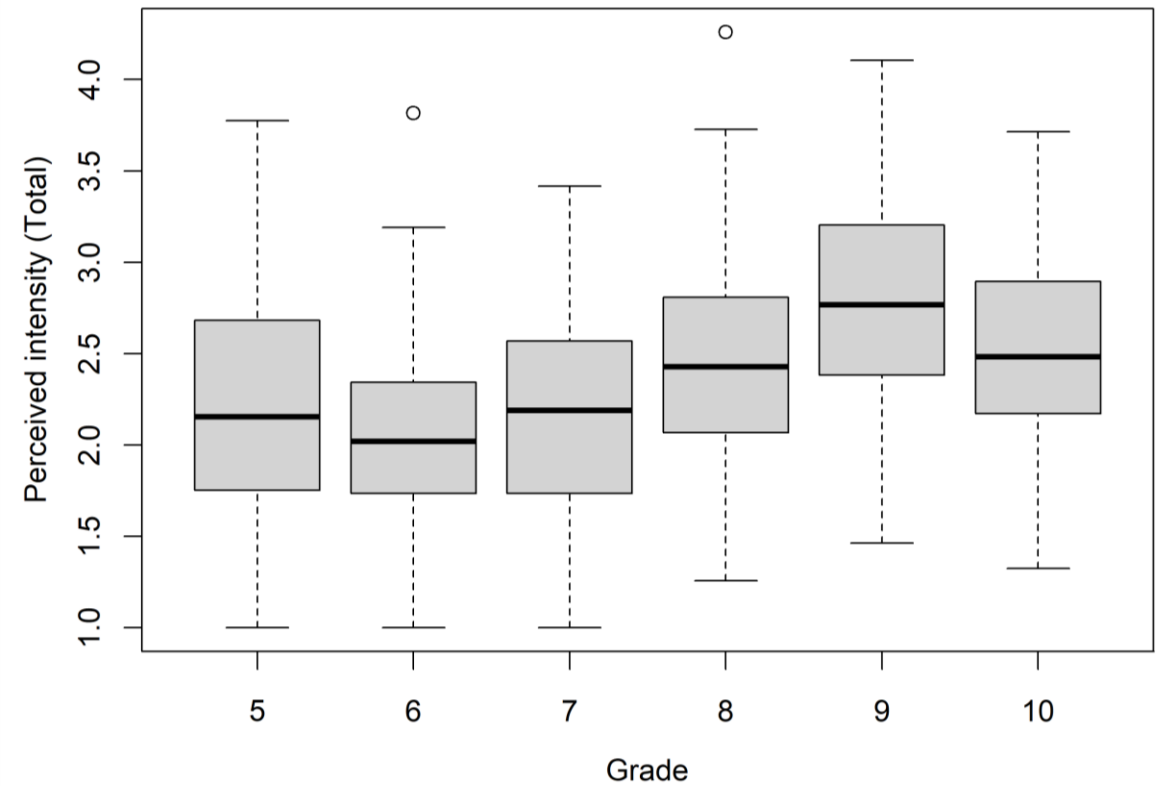

Figure 27: Total Technostress Level Dependent on the Adolescents' Grade

The correlations in Table 30 are more nuanced for the number of owned devices. Although they indicate that there are negative associations with all technostress creators, this effect only seems to be significant for *Complexity*, *Disclosure*, *Uncertainty*, and *Insecurity*.

Analysis of the Technostress Creators

Our results show that for adolescents, a broader set of technostress creators is relevant than studies on technostress of employees commonly consider (Ayyagari et al. 2011; Ragu-Nathan et al. 2008). *Disclosure* and *Unreliability* are the most pronounced technostress creators for adolescents – *Unreliability* is also well-known from studies of technostress at the workplace (Ayyagari et al. 2011). Unlike studies of technostress at the workplace, we find that *Social Pressure* plays a role in adolescents' technostress perception. These technostress creators might be more pronounced for adolescents than for adults and more pronounced for a private context compared to a work context. Nevertheless, our results suggest that studies of technostress at the workplace might also consider *Social Pressure* as a technostress creator. Other well-known technostress creators at the workplace (*Uncertainty, Insecurity, Complexity*) also seem to put demands on adolescents but with comparably low intensity.

In line with other studies (Lutz et al. 2014; Weinstein and Selman 2016a), we find that the intensity of technostress is higher for girls than for boys. However, some studies focusing on adults report the opposite effect (Ragu-Nathan et al. 2008). Although adolescents' ICT competency should increase with age, our study yields that older adolescents tend to perceive a higher intensity of technostress than younger adolescents. This might indicate that ICT use puts disproportionately higher demands on older adolescents, and the increase in technology competency does not compensate for this divide.

The following sections illuminate the individual technostress creators in more detail. Since there is little literature on technostress among adolescents, we enrich our findings based on qualitative feedback provided by adolescents and teachers in Study 1 and the lessons preceding the survey in Study 2. As the difference between genders applies to all technostress creators, we leave this aspect in the following discussion aside.

Disclosure

Disclosure is the technostress creator with the highest mean value (mean = 3.04) in our study and, thus, supposedly the most prevalent cause of technostress for adolescents. One reason might be that the handling of personal data on the internet or social media enjoys close attention in media, school, and at home. Adolescents often have a higher awareness of the consequences of disclosing information online than adults (Christofides et al. 2012). This awareness serves as the strongest predictor for information control on Facebook (Christofides et al. 2012). These insights show that adolescents attach great importance to prevent the *Disclosure* of information, which apparently is a task straining their resources. Adolescents' contributions in the lessons suggest that many of them have already experienced or witnessed the effects of data misuse and can give a multitude of examples ranging from unwanted advertising to social networks selling personal data. In our research, we observe a rising intensity of the technostress creator with increasing age and grade. This could indicate that younger adolescents do not yet have a good grasp of digital and social media and are still in the process of developing a sense of privacy and the value of data.

Unreliability

Another major technostress creator for adolescents is *Unreliability* (mean = 2.77). Unreliable ICT is not only a major annoyance at the workplace (Kalischko et al. 2020) but transfers to the private use of ICT by adolescents. In the lessons, the adolescents provided many examples of situations in which unreliable ICT caused technostress and associated negative emotions with these events. Frequently mentioned situations include incorrect battery displays on smartphones, problems with the internet connection at home or on the way, and unreliable information on websites when working on school projects. As for most technostress creators, older adolescents perceive a higher intensity of *Unreliability*, which might be traced back to the more purposeful use of ICT in which technological hassle is perceived as more intense.

Uncertainty

With a perceived intensity of 2.44, *Uncertainty* is in the middle range of the technostress creators. Like few other technostress creators, it exhibits a significant negative correlation with the number of owned devices. This indicates that, although affected more by updates and technological changes, adolescents who have a high number of devices tend to perceive these changes as less demanding than adolescents with few devices. A possible interpretation could be that they are already used to frequent changes and, thus, do not experience these events as overly demanding. Several adolescents stated in the lessons that they perceive only major updates that involve changes to the user interface and functionality as demanding, whereas smaller updates are an everyday occurrence to them.

Insecurity

Although finding a job is still quite far into the future for many of the adolescents participating in our study, we find that adolescents, to some extent, are concerned about their future workplace and perceive a moderate level of technostress due to *Insecurity* (mean = 2.34). Not surprisingly, this technostress creator depends significantly on grade and rises from a median of 2 in fifth to seventh grades to 3 in the ninth grade. In the lessons, adolescents in lower grades often positively dreamed of a world in which ICT took over all the work, and no one had to work anymore, whereas adolescents in higher grades tended to worry about being substituted by ICT and evaluated this scenario as disconcerting.

Social Pressure

Social Pressure (mean = 2.13) is among the least relevant technostress creators in our study. This finding is rather surprising because the perceived need to be constantly available, as a facet of *Social Pressure*, has been found to put high demands on adolescents, especially the younger ones (Reinecke et al. 2017). Although it is important for adolescents to identify with a group and build strong ties to their peers, the participants of our study apparently perceive comparably little stress resulting from the need to assimilate to their peers' ICT use and adopt specific behavioral patterns. Adolescents stated in the lessons that they use the same social networks as their peers or buy the same video games in order to play with their peers but do so voluntarily and with positive feelings. Although *Social Pressure* statistically is more relevant among female adolescents, exemplary situations in which girls perceive this technostress creator were scarce in the lessons. However, this might, of course, be due to reservations about expressing personal preferences and critique of the social environment when their peers are present. Literature suggests various reasons why girls perceive higher technostress in this category. One reason could be that they feel the constant need to present the best of themselves in social media (Fardouly et al. 2015). Another explanation might be that girls are more susceptible to suffer from the "fear of missing out" (Franchina et al. 2018), that is, the "pervasive apprehension that others might be having rewarding experiences from which one is absent" (Przybylski et al. 2013, p. 1841).

Complexity

Complexity seems to cause the least technostress in adolescents, with an average intensity of only 1.71. Compared to studies focusing on adults (Maier et al. 2015b; Tarafdar et al. 2011), this finding indicates that adolescents consider the complexity of ICT to be less stressful than adults do. Although several studies criticize the simplistic assumption that "digital natives" would generally have better technological expertise than people who have acquired technological skills at an older age (Helsper and Eynon 2010), our results indicate that generational differences in the perception of *Complexity* exist. Adolescents reported only a few scenarios in which they considered ICT as complex (e.g., switching from iOS to Android) but repeatedly stated they perceived it as demanding to help parents and grandparents overcome problems with ICT recurrently. Another interesting finding is that *Complexity* is one of the few technostress creators that exhibit a significant correlation with the number of devices an adolescent owns. According to our study, the more devices an adolescent owns, the less intensity they attribute to *Complexity*. The causality might be either way or bidirectional.

Appendix B.3 – Adolescents' Activation of Coping Responses

Category (Study 1)	ID	Coping Response	Mean	Med.	SD
Emotion regulation	E1	Talk with others about own TS perception	2.17	2	1.14
	E2	Engage in activities with family and friends	2.76	3	1.24
	E3	Distract oneself	3.31	4	1.30
	E4	Sleep more than usual	2.13	2	1.21
	E5	Talk oneself into believing to have no TS	1.85	1	1.10
	E6	Seek professional help	1.29	1	0.80
Knowledge acquisition	K1	Respect parents' advice on how to use ICT	2.71	3	1.33
	K2	Educate oneself on how to prevent TS	2.02	2	1.14
	K3	Read privacy policies	1.91	1	1.17
	K4	Remember advice from school on how to use ICT	2.55	3	1.24
	K5	Take time to learn how to use new ICT	2.56	2	1.28
	K6	Try to understand what causes TS in oneself	2.20	2	1.20
Behavior adaptation	B1	Discontinue use of specific ICT	2.59	3	1.31
	B2	Avoid aggressiveness in ICT	2.85	3	1.40
	B3	Limit oneself to a single device	2.53	2	1.31
	B4	Leave the smartphone at home	2.44	2	1.45
	B5	Seek personal contact	3.20	3	1.32
	B6	Select social networks carefully	3.56	4	1.34
Technology adaptation	T1	Delete social network accounts	2.23	2	1.32
	T2	Adjust privacy settings	3.35	4	1.52
	T3	Mute chat groups	3.03	3	1.46
	T4	Activate silent or flight mode	3.53	4	1.28
	T5	Prevent sleep disturbances by ICT	3.09	3	1.55
	T6	Remove unneeded apps or files	3.70	4	1.33
Social rules	R1	Follow parents' time restrictions for ICT use	2.87	3	1.38
	R2	Follow parents' rules regarding ICT content	2.99	3	1.52
	R3	Follow parents' device rules for ICT use	3.30	4	1.52
	R4	Buy ICT on one's own	2.64	3	1.42
	R5	Make rules with friends about ICT use	2.19	2	1.25
	R6	Follow school rules for ICT use	3.62	4	1.45

Table 31: Descriptive Statistics of Coping Responses

Appendix B.4 – Detailed Results of the Exploratory Factor Analysis

Table 32 displays the EFA's factor loadings of the coping responses based on oblimin rotation using a significant factor criterion of .4 (Hair et al. 1998). Three coping responses (*T1*, *E1*, *B2*) do not load sufficiently on any factor and are excluded from further analysis. The coping response *T2* loads on two factors.

		Factors (Study 2)				
Coping Category (Study 1)	**ID**	**Avoid Stressful ICT**	**Follow the Rules**	**Use ICT Consciously**	**Contain Negative Emotions**	**Acquire ICT**
Technology adaptation	T1					
	T2	0.444				0.405
	T3	0.546				
	T4	0.699				
	T5	0.470				
	T6	0.641				
Social rules	R1		0.806			
	R2		0.891			
	R3		0.824			
	R4					0.782
	R5				0.460	
	R6		0.629			
Knowledge acquisition	K1		0.440			
	K2			0.750		
	K3			0.757		
	K4			0.418		
	K5			0.504		
	K6			0.500		
Emotion regulation	E1					
	E2	0.549				
	E3	0.653				
	E4				0.478	
	E5				0.582	
	E6				0.572	
Behavior adaptation	B1				0.449	
	B2					
	B3				0.458	
	B4		0.400			
	B5	0.544				
	B6	0.615				
Eigenvalues		3.741	3.305	2.445	2.310	1.533
% of variance		12.5	11.0	8.1	7.7	5.1

Note: Loadings < .4 not shown

Table 32: Factor Loadings of Coping Responses

Appendix B.5 – Robustness Check of Results Relating to Gender

CP	ID	Coping Response	Gender (overall)	Gender (subsample)
Avoid Stressful ICT	E2	Engage in activities with family and friends	**.185****	.103
	E3	Distract oneself	**.301*****	**.218****
	B5	Seek personal contact	**.265*****	**.279*****
	B6	Select social networks carefully	**.182****	.113
	T2	Adjust privacy settings	**.234*****	.146·
	T3	Mute chat groups	**.182****	.106
	T4	Activate silent or flight mode	**.225*****	**.176***
	T5	Prevent sleep disturbances by ICT	**.207****	**.232****
	T6	Remove unneeded apps or files	**.140***	.156·
Follow the Rules	R1	Follow parents' time restrictions for ICT use	-.039	-.037
	R2	Follow parents' rules regarding ICT content	-.102	-.126
	R3	Follow parents' rules regarding device use	.006	-.002
	R6	Follow school rules for ICT use	.009	-.038
	K1	Respect parents' advice on how to use ICT	.004	-.037
	B4	Leave the smartphone at home	.017	-.011
Use ICT Consciously	K2	Educate oneself on how to prevent TS	**-.133***	-.147·
	K3	Read privacy policies	-.004	.121
	K4	Remember school advice on how to use ICT	.072	-.037
	K5	Take time to learn how to use new ICT	**-.149***	-.108
	K6	Try to understand what causes TS in oneself	.090	**.172***
Contain Negative Emotions	E4	Sleep more than usual	**.181****	.143·
	E5	Talk oneself into believing to have no TS	**.248*****	**.245****
	E6	Seek professional help	-.094	-.130
	B1	Discontinue use of specific ICT	**.211****	**.221****
	B3	Limit oneself to a single device	**.232*****	**.196***
	R5	Make rules with friends about ICT use	.101	.159·
Acquire ICT	R4	Buy ICT on one's own	-.048	-.087
No sig. loadings	T1	Delete social network accounts	.059	.023
	E1	Talk with others about own TS perception	.070	-.010
	B2	Avoid aggressiveness in ICT	**.224*****	.145·

Notes: Significance codes: *** = p < .001, ** = p < .01, * = p < .05, .= p < .1
"Gender (subsample)" reports the results of the robustness check with the urban higher educational secondary school

Table 33: Point-Biserial Correlations of Coping Responses with Demographic Data

Appendix C – Composing a Design Theory for Mobile Stress Assessment

Appendix C.1 – Analysis of MSA Literature

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
1	Liao et al. (2005) - A Real-Time Human Stress Monitoring System Using Dynamic Bayesian Network	Mixed	Obtrusive	Continuously	Metric	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
2	Ma et al. (2010) - Development of an ambulatory multi-parameter monitoring system for physiological stress related parameters	Mixed	Unobtrusive	Continuously	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
3	Setz et al. (2010) - Discriminating stress from cognitive load using a wearable eda device	Biological Symptoms	Unobtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
4	Hosseini and Khalilzadeh (2010) - Emotional Stress Recognition System Using EEG and Psychophysiological Signals: Using New Labelling Process of EEG Signals in Emotional Stress State	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
5	Rachuri et al. (2010) - EmotionSense: A Mobile Phones Based Adaptive Platform for Experimental Social Psychology Research	Behavioral Symptoms	Unobtrusive	Continually	Ordinal	Single Device	Non-Personal and Raw Personal Data
6	Pioggia et al. (2010) - Interreality: The use of advanced technologies in the assessment and treatment of psychological stress	Mixed	Obtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Raw Personal Data
7	Sanches et al. (2010) - Mind the body!: designing a mobile stress management application encouraging personal reflection	Biological Symptoms	Unobtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
8	Shi et al. (2010) - Personalized Stress Detection from Physiological Measurements.	Biological Symptoms	Unobtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
9	Adams et al. (2010) - Towards Personal Stress Informatics: Comparing Minimally Invasive Techniques for Measuring Daily Stress in the Wild	Mixed	Unobtrusive	Continually	Ordinal	Single Device	Non-Personal and Raw Personal Data
10	Berndt et al. (2011) - A scalable and secure Telematics Platform for the hosting of telemedical applications. Case study of a stress and fitness monitoring	Biological Symptoms	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
11	Sierra et al. (2011) - A Stress-Detection System Based on Physiological Signals and Fuzzy Logic	Biological Symptoms	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
12	Singh et al. (2011) - An approach for real-time stress-trend detection using physiological signals in wearable computing systems for automotive drivers	Biological Symptoms	Unobtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
13	Adnane et al. (2011) - An automated program for mental stress and apnea/hypopnea events detection	Mixed	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
14	Lefter et al. (2011) - Automatic stress dectection in emergency telephone calls	Behavioral Symptoms	Life-integrated	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
15	Lane et al. (2011) - BeWell: A Smartphone Application to Monitor, Model and Promote Wellbeing	Mixed	Life-integrated	Regular Intervals	Binary	Multi-Platform-System	Non-Personal and Raw Personal Data
16	Plarre et al. (2011) - Continuous Inference of Psychological Stress from Sensory Measurements Collected in the Natural Environment	Biological Symptoms	Unobtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
17	Massot et al. (2011) - EmoSense: An Ambulatory Device for the Assessment of ANS Activity - Application in the Objective Evaluation of Stress With the Blind	Biological Symptoms	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
18	Dickerson et al. (2011) - Empath: a continuous remote emotional health monitoring system for depressive illness	Mixed	Unobtrusive	Regular Intervals	Metric	Multi-Platform-System	Non-Personal and Raw Personal Data
19	Chang et al. (2011) - How’s My Mood and Stress?: An Efficient Speech Analysis Library for Unobtrusive Monitoring on Mobile Phones	Behavioral Symptoms	Unobtrusive	Regular Intervals	Binary	Single Device	Non-Personal and Raw Personal Data
20	Yoo and Lee (2011) - Mental stress assessment based on pulse photoplethysmography	Biological Symptoms	Obtrusive	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
21	Mokhayeri et al. (2011) - Mental stress detection using physiological signals based on soft computing techniques	Mixed	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
22	Jovanov et al. (2011) - Real-time monitoring of occupational stress of nurses	Mixed	Unobtrusive	Continuously	Ordinal	Multi-Platform-System	Non-Personal and Raw Personal Data
23	Choi and Gutierrez-Osuna (2011) - Removal of Respiratory Influences From Heart Rate Variability in Stress Monitoring	Biological Symptoms	Obtrusive	Regular Intervals	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
24	Sierra & del Pozo (2011) - Stress detection by means of stress physiological template	Biological Symptoms	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
25	Wijsman et al. (2011) - Towards mental stress detection using wearable physiological sensors	Biological Symptoms	Unobtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
26	Bakker et al. (2011) - What's Your Current Stress Level? Detection of Stress Patterns from GSR Sensor Data	Biological Symptoms	Obtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
27	Paschero et al. (2012) - A real time classifier for emotion and stress recognition in a vehicle driver	Behavioral Symptoms	Unobtrusive	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
28	Singh et al. (2012) - Biosignal based on-road stress monitoring for automotive drivers	Biological Symptoms	Unobtrusive	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
29	Bauer and Lukowicz (2012) - Can smartphones detect stress-related changes in the behaviour of individuals?	Mixed	Unobtrusive	Regular Intervals	Binary	Single Device	Non-Personal and Raw Personal Data
30	Zhang et al. (2012) - deStress - Mobile and remote stress monitoring, alleviation, and management platform	Biological Symptoms	Unobtrusive	Continuously	Metric	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
31	Choi et al. (2012) - Development and Evaluation of an Ambulatory Stress Monitor Based on Wearable Sensors	Mixed	Unobtrusive	Continuously	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
32	Ayzenberg et al. (2012) - FEEL: Frequent EDA and Event Logging - A Mobile Social Interaction Stress Monitoring System	Mixed	Unobtrusive	Continuously	Ordinal	Multi-Platform-System	Non-Personal and Raw Personal Data
33	Zheng et al. (2012) - Human emotional stress assessment through Heart Rate Detection in a customized protocol experiment	Mixed	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
34	Tartarisco et al. (2012) - Personal Health System architecture for stress monitoring and support to clinical decisions	Mixed	Unobtrusive	Regular Intervals	Binary	Multi-Platform-System	Non-Personal and Raw Personal Data
35	Lu et al. (2012) - StressSense: Detecting Stress in Unconstrained Acoustic Environments Using Smartphones	Behavioral Symptoms	Unobtrusive	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
36	Lee et al. (2012) - Towards Unobtrusive Emotion Recognition for Affective Social Communication	Mixed	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Raw Personal Data
37	Giakoumis et al. (2012) - Using activity-related behavioural features towards more effective automatic stress detection	Mixed	Obtrusive	Continuously	Metric	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
38	Vidal et al. (2012) - Wearable eye tracking for mental health monitoring	Mixed	Obtrusive	Regular Intervals	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
39	Gaggiolo et al. (2013) - A mobile data collection platform for mental health research	Mixed	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
40	Zhao et al. (2013) - A Pervasive Stress Monitoring System Based on Biological Signals	Biological Symptoms	Obtrusive	Continuously	Metric	Multi-Platform-System	Non-Personal and Aggregated Personal Data
41	Sharma et al. (2013) - Modeling stress using thermal facial patterns: A spatio-temporal approach	Biological Symptoms	Unobtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
42	Kusserow et al. (2013) - Monitoring Stress Arousal in the Wild	Mixed	Life-integrated	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal Data
43	LiKamWa et al. (2013) - MoodScope: Building a Mood Sensor from Smartphone Usage Patterns	Behavioral Symptoms	Unobtrusive	Continually	Ordinal	Single Device	Non-Personal and Raw Personal Data
44	Bousefsaf et al. (2013) - Remote assessment of the heart rate variability to detect mental stress	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
45	Kocielnik et al. (2013) - Smart technologies for long-term stress monitoring at work	Mixed	Unobtrusive	Regular Intervals	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
46	Weppner et al. (2013) - Smartphone Based Experience Sampling of Stress-Related Events	Introspection	Unobtrusive	Continually	Binary	Single Device	Non-Personal and Aggregated Personal Data
47	Kurniawan et al. (2013) - Stress detection from speech and Galvanic Skin Response signals	Mixed	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
48	Picard and Sano (2013) - Stress Recognition Using Wearable Sensors and Mobile Phones	Mixed	Unobtrusive	Continually	Ordinal	Single Device	Non-Personal and Aggregated Personal Data
49	Muaremi et al. (2013) - Towards Measuring Stress with Smartphones and Wearable Devices During Workday and Sleep	Mixed	Unobtrusive	Regular Intervals	Ordinal	Multi-Platform-System	Non-Personal and Raw Personal Data
50	Khan et al. (2013) - Using an ambulatory stress monitoring device to identify relaxation due to untrained deep breathing	Mixed	Obtrusive	Regular Intervals	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
51	Okada et al. (2013) - Wearable ECG recorder with acceleration sensors for monitoring daily stress: Office work simulation study	Biological Symptoms	Unobtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
52	Manousos et al. (2014) - Contactless detection of facial signs related to stress: A preliminary study	Behavioral Symptoms	Obtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
53	Bogomolov et al. (2014) - Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits	Mixed	Life-integrated	Continuously	Binary	Single Device	Non-Personal and Raw Personal Data
54	Gao et al. (2014) - Detecting emotional stress from facial expressions for driving safety	Behavioral Symptoms	Life-integrated	Continuously	Metric	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
55	Chen et al. (2014) - Detection of Psychological Stress Using a Hyperspectral Imaging Technique	Biological Symptoms	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
56	Wang et al. (2014) - StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones	Mixed	Unobtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Raw Personal Data
57	Rodrigues et al. (2015) - A Mobile Sensing Approach to Stress Detection and Memory Activation for Public Bus Drivers	Mixed	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
58	Rodellar-Biarge et al. (2015) - Analysis of emotional stress in voice for deception detection	Biological Symptoms	Unobtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
59	Mohino-Herranz et al. (2015) - Assessment of Mental, Emotional and Physical Stress through Analysis of Physiological Signals Using Smartphones	Biological Symptoms	Unobtrusive	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
60	Gjoreski et al. (2015) - Automatic Detection of Perceived Stress in Campus Students Using Smartphones	Mixed	Unobtrusive	Continually	Ordinal	Single Device	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
61	Mayya et al. (2015) - Continuous monitoring of stress on smartphone using heart rate variability	Biological Symptoms	Unobtrusive	Continuously	Metric	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
62	Hovsepian et al. (2015) - cStress: Towards a Gold Standard for Continuous Stress Assessment in the Mobile Environment	Mixed	Unobtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
63	Munla et al. (2015) - Driver stress level detection using HRV analysis	Biological Symptoms	Unobtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
64	Huang et al. (2015) - Emotion Map - A Location-Based Mobile Social System for Improving Emotion Awareness and Regulation	Introspection	Unobtrusive	Regular Intervals	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
65	Tivatansakul and Ohkura (2015) - Improvement of emotional healthcare system with stress detection from ECG signal	Mixed	Obtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
66	Ferdous et al. (2015) - Investigating correlation between verbal interactions and perceived stress	Behavioral Symptoms	Obtrusive	Regular Intervals	Binary	Single Device	Non-Personal and Raw Personal Data
67	Ciman et al. (2015) - iSenseStress Assessing stress through human-smartphone interaction analysis	Behavioral Symptoms	Unobtrusive	Continually	Ordinal	Single Device	Non-Personal and Raw Personal Data
68	Ghaderi et al. (2015) - Machine learning-based signal processing using physiological signals for stress detection	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
69	Sandulescu et al. (2015) - Mobile app for stress monitoring using voice features	Behavioral Symptoms	Unobtrusive	Continually	Ordinal	Single Device	Non-Personal and Raw Personal Data
70	Aigrain et al. (2015) - Person-specific behavioural features for automatic stress detection	Behavioral Symptoms	Unobtrusive	Regular Intervals	Ordinal	Single Device	Non-Personal and Aggregated Personal Data
71	Bogomolov et al. (2015) - Pervasive stress recognition for sustainable living	Mixed	Obtrusive	Regular Intervals	Ordinal	Single Device	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
72	Bin et al. (2015) - Real-time personalized stress detection from physiological signals	Mixed	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
73	Sano et al. (2015) - Recognizing academic performance, sleep quality, stress level, and mental health using personality traits, wearable sensors and mobile phones	Mixed	Unobtrusive	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
74	Lefter et al. (2015) - Recognizing stress using semantics and modulation of speech and gestures	Behavioral Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
75	Hu et al. (2015) - Signal Quality Assessment Model for Wearable EEG Sensor on Prediction of Mental Stress	Biological Symptoms	Unobtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
76	Zubair et al. (2015) - Smart Wearable Band for Stress Detection	Biological Symptoms	Unobtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
77	Sioni and Chittaro (2015) - Stress Detection Using Physiological Sensors	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
78	Widanti et al. (2015) - Stress Level Detection using Heart Rate, Blood Pressure, and GSR and Stress Therapy by Utilizing Infrared	Biological Symptoms	Obtrusive	Regular Intervals	Metric	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
79	Ahmed et al. (2016) - A Calibration Protocol that Improves Stress/Relax Classification by Relabeling Deep Breathing Relaxation Exercises	Behavioral Symptoms	Unobtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
80	Attaran et al. (2016) - A low-power multi-physiological monitoring processor for stress detection	Mixed	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
81	Garcia-Ceja et al. (2016) - Automatic Stress Detection in Working Environments From Smartphone - Accelerometer Data: A First Step	Behavioral Symptoms	Unobtrusive	Continually	Binary	Single Device	Non-Personal and Raw Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
82	Zenonos et al. (2016) - HealthyOffice: Mood recognition at work using smartphones and wearable sensors	Biological Symptoms	Unobtrusive	Regular Intervals	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
83	Ciman and Wac (2016) - Individuals Stress Assessment Using Human-Smartphone Interaction Analysis	Behavioral Symptoms	Unobtrusive	Continually	Ordinal	Single Device	Non-Personal and Raw Personal Data
84	Keshan et al. (2016) - Machine learning for stress detection from ECG signals in automobile drivers	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
85	Aigrain et al. (2016) - Multimodal stress detection from multiple assessments	Mixed	Unobtrusive	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
86	Sinha et al. (2016) - Physiological sensing based stress analysis during assessment	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
87	Roveda et al. (2016) - Psychological health monitoring for pilots and astronauts by tracking sleep-stress-emotion changes	Mixed	Obtrusive	Regular Intervals	Ordinal	Multi-Platform-System	Non-Personal and Raw Personal Data
88	Lee et al. (2016) - Stress Events Detection of Driver by Wearable Glove System	Biological Symptoms	Unobtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
89	Ashok et al. (2016) - Validation of Stress Assessment using Mobile Phone	Behavioral Symptoms	Unobtrusive	Continually	Binary	Single Device	Non-Personal and Raw Personal Data
90	Lebepe et al. (2016) - Wearable stress monitoring system using multiple sensors	Biological Symptoms	Unobtrusive	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
91	Sandulescu and Dobrescu (2016) - Wearable system for stress monitoring of firefighters in special missions	Mixed	Unobtrusive	Regular Intervals	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
92	Cho (2017) - Automated mental stress recognition through mobile thermal imaging	Biological Symptoms	Obtrusive	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
93	Cho et al. (2017) - DeepBreath: Deep learning of breathing patterns for automatic stress recognition using low-cost thermal imaging in unconstrained settings	Behavioral Symptoms	Obtrusive	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
94	Tripathi and Mishra (2017) - Design and implementation of a real time stress monitoring system with the help of ECG using Matlab tool	Biological Symptoms	Unobtrusive	Continuously	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
95	Pandey (2017) - Machine Learning and IoT for prediction and detection of stress	Biological Symptoms	Unobtrusive	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
96	Subhani et al. (2017) - Machine Learning Framework for the Detection of Mental Stress at Multiple Levels	Biological Symptoms	Life-integrated	Continually	Binary	Multi-Platform-System	Non-Personal and Raw Personal Data
97	Mokhayeri and Akbarzadeh (2017) - Mental Stress Detection Based on Soft Computing Techniques	Behavioral Symptoms	Obtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Raw Personal Data
98	Simões et al. (2017) - Mobile application for stress assessment	Biological Symptoms	Unobtrusive	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
99	Ciabattoni et al. (2017) - Real-time mental stress detection based on smartwatch	Biological Symptoms	Unobtrusive	Continuously	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
100	Zhang et al. (2017) - Recognition of Real-Scene Stress in Examination with Heart Rate Features	Biological Symptoms	Obtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
101	Sevil et al. (2017) - Social and competition stress detection with wristband physiological signals	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
102	Cemat et al. (2017) - Stress influence on drivers identified by monitoring galvanic skin resistance and heart rate variability	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
103	Jáuregui et al. (2017) - Toward automatic detection of acute stress: Relevant nonverbal behaviors and impact of personality traits	Mixed	Obtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal Data
104	Choi et al. (2017) - Wearable Device-Based System to Monitor a Driver - Stress, Fatigue, and Drowsiness	Biological Symptoms	Unobtrusive	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
105	Lee et al. (2017) - Wearable Glove-Type Driver Stress Detection Using a Motion Sensor	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
106	Lawanont and Inoue (2018) - An unsupervised learning method for perceived stress level recognition based on office working behavior	Mixed	Life-integrated	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
107	Arkhangelsky et al. (2018) - Development and analysis of analog-digital neural net for speech stress detection	Behavioral Symptoms	Unobtrusive	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal Data
108	Attaran et al. (2018) - Embedded Low-Power Processor for Personalized Stress Detection	Biological Symptoms	Unobtrusive	Regular Intervals	Binary	Single Device	Non-Personal and Aggregated Personal Data
109	Gaikwad and Paithane (2018) - Novel approach for stress recognition using EEG signal by SVM classifier	Biological Symptoms	Obtrusive	Regular Intervals	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
110	Wu et al. (2018) - Quantitative Assessment for Self-Tracking of Acute Stress based on Triangulation Principle in a Wearable Sensor System	Biological Symptoms	Obtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal and Aggregated Personal Data
111	Boateng and Kotz (2018) - StressAware: An app for real-time stress monitoring on the amulet wearable platform	Biological Symptoms	Unobtrusive	Continually	Metric	Multi-Platform-System	Non-Personal and Aggregated Personal Data
112	Maaoui and Pruski (2018) - Unsupervised stress detection from remote physiological signal	Behavioral Symptoms	Obtrusive	Continually	Binary	Multiple Devices using Local Communication	Non-Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
113	Ciman and Wac (2018) - Individuals' Stress Assessment Using Human-Smartphone Interaction Analysis	Mixed	Life-integrated	Continually	Ordinal	Multiple Devices using Local Communication	Non-Personal Data
114	Koldijk et al. (2018) - Detecting Work Stress in Offices by Combining Unobtrusive Sensors	Mixed	Unobtrusive	Regular Intervals	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
115	Almogbel et al. (2018) - EEG-Signals Based Cognitive Workload Detection of Vehicle Driver using Deep Learning	Biological Symptoms	Unobtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
116	Wu et al. (2018) - Quantitative Assessment for Self-Tracking of Acute Stress Based on Triangulation Principle in a Wearable Sensor System	Mixed	Unobtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
117	Viegas et al. (2018) - Towards Independent Stress Detection: a Dependent Model using Facial Action Units	Behavioral Symptoms	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
118	Vuppalapati et al. (2018) - A System to Detect Mental Stress Using Machine Learning and Mobile Development	Biological Symptoms	Unobtrusive	Continually	Metric	Multi-Platform-System	Non-Personal and Raw Personal Data
119	Park et al. (2018) - Prediction of Daily Mental Stress Levels Using a Wearable Photoplethysmography Sensor	Biological Symptoms	Unobtrusive	Continuously	Metric	Multi-Platform-System	Non-Personal and Aggregated Personal Data
120	Dobbins and Fairclough (2019) - Signal Processing of Multimodal Mobile Lifelogging Data Towards Detecting Stress in Real-World Driving	Mixed	Life-integrated	Continually	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
121	Gurel et al. (2019) - Fusing Near-Infrared Spectroscopy With Wearable Hemodynamic Measurements Improves Classification of Mental Stress	Biological Symptoms	Obtrusive	Regular Intervals	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
122	Kashevnik et al. (2019) - Dangerous Situations Determination by Smartphone in Vehicle Cabin: Classification and Algorithms	Mixed	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Raw Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
123	Rachakonda et al. (2019) - Stress-Lysis: A DNN-Integrated Edge Device for Stress Level Detection in the IoMT	Biological Symptoms	Unobtrusive	Continually	Metric	Multi-Platform-System	Non-Personal and Raw Personal Data
124	Yu et al. (2019) - An Unobtrusive Stress Recognition System for the Smart Office	Mixed	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
125	Momeni et al. (2019) - Real-Time Cognitive Workload Monitoring Based on Machine Learning Using Physiological Signals in Rescue Missions	Biological Symptoms	Unobtrusive	Continually	Metric	Multi-Platform-System	Non-Personal and Aggregated Personal Data
126	Pernice et al. (2019) - Minimally Invasive Assessment of Mental Stress based on Wearable Wireless Physiological Sensors and Multivariate Biosignal Processing	Biological Symptoms	Obtrusive	Regular Intervals	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
127	Nita et al. (2019) - A Body Area Network for Ubiquitous Driver Stress Monitoring based on ECG Signal	Biological Symptoms	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
128	Ghosh et al. (2019) - Representation Learning for Emotion Recognition from Smartphone Keyboard Interactions	Mixed	Life-integrated	Continuously	Ordinal	Multiple Devices using Local Communication	Non-Personal Data
129	Maxhuni et al. (2019) - Unobtrusive Stress Assessment Using Smartphones	Mixed	Life-integrated	Continuously	Metric	Multi-Platform-System	Non-Personal Data
130	Wang et al. (2019) - Assessing Mental Stress Based on Smartphone Sensing Data: An Empirical Study	Mixed	Life-integrated	Continuously	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
131	Anusha et al. (2020) - Electrodermal Activity Based Pre-surgery Stress Detection Using a Wrist Wearable	Biological Symptoms	Unobtrusive	Continually	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
132	Can et al. (2020) - Personal Stress-Level Clustering and Decision-Level Smoothing to Enhance the Performance of Ambulatory Stress Detection With Smartwatches	Mixed	Unobtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data

ID	Research Article	Stress Correlates	Visibility for the User	Assessment Frequency	Assessment Scale	Ecosystem	Privacy
133	Delmastro et al. (2020) - Cognitive Training and Stress Detection in MCI Frail Older People Through Wearable Sensors and Machine Learning	Biological Symptoms	Unobtrusive	Continually	Binary	Multi-Platform-System	Non-Personal and Aggregated Personal Data
134	Arpaia et al. (2020) - A Wearable EEG Instrument for Real-Time Frontal Asymmetry Monitoring in Worker Stress Analysis	Biological Symptoms	Unobtrusive	Continuously	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
135	Vaishali et al. (2020) - HRV based Stress Assessment of Individuals in a Work Environment	Biological Symptoms	Unobtrusive	Continuously	Ordinal	Multi-Platform-System	Non-Personal and Aggregated Personal Data
136	Tundis et al. (2020) - Human Physical Status detection related to Danger Situations based on Smartwatch and Smartphone	Mixed	Life-integrated	Continuously	Metric	Multi-Platform-System	Non-Personal and Aggregated Personal Data

Table 34: Analysis of MSA Literature (n = 136 Studies)

Appendix C.2 – MSA Prototypes

To gain practical experience on MSA design by ourselves, we developed five prototypical MSA systems for different use cases. During the agile development processes and within the studies evaluating our prototypes, we gained important insights that help us understand our design theory's interconnectedness and reveal possible trade-offs that need to be considered in the design process. Each prototype is described in the following structure. It introduces a specific application scenario, outlines the flexible design and development of the prototype, presents the empirical study setting and relevant results, and discusses important learnings from this process.

Prototype 1 – Life-Integrated Mobile Stress Assessment

***Application Scenario*:** This prototype targets the real-time assessment of perceived stress using only the sensors of a personal smartphone to infer the user's stress level on an interval scale while being best possibly integrated into their life. Here we provide a brief overview of the system. A detailed description is provided in Gimpel et al. (2019b).

Design & Development: We implemented a prototype for the Android operating system, tested it with alpha and beta testers within several development and deployment cycles, and iteratively refined it based on testers' feedback. It reads a total of 36 hardware and software smartphone sensors to identify sensors that might be applicable for stress detection empirically. Exemplary sensors include ambient temperature, audio frequency, and amplitude, an analysis of the user's voice during phone calls, the frequency of pressing the power button, or the number of incoming or outgoing text messages. With respect to the design features, the prototype collects mixed data (DF1) combining aggregated behavioral and environmental facets (DF6) to achieve a life-integrated (DF2), continuous (DF3) metric (DF4) stress assessment on a single device (DF5).

Empirical Study: We applied the prototype within the context of a public field study with 40 participants from countries across the globe and collected a total of 474 stress level observations (average of 11 observations per participant). For calibration purposes within the study and related smartphone sensors to perceived stress, the prototype also asks users to answer a short questionnaire three times a day. The prototype stores data on the device and regularly transmits it to a server. It uses supervised offline machine learning relating perceived stress to sensor data. Data analysis showed that the smartphone sensor data captured by the prototype sufficed to explain 41% of the variance in perceived stress levels (R^2 using elastic net regression based on 474 answered questionnaires from 40 participants). For more details, see Gimpel et al. (2019b).

Learnings: The prototype's successful development suggests that the design's implementation is generally feasible, even for an advanced use case. However, the prototype also unveils important learnings for the design of MSA systems. For example, first interviews with test users revealed issues such as high battery consumption and a significant decrease in the battery's state of charge. This issue was the result of a probe interval of sensors being set to only a few seconds. We further learned that a high level of life integration is vital for user acceptance of frequent stress assessment. For model building, the prototype also required uploading the data to cloud storage. We chose the upload interval as a trade-off between data timeliness and resource usage, and limited uploading to times when Wi-Fi is available to spare data connection. We eliminated very sensitive data (e.g., text messages) stored in the first versions from the final instantiation due to privacy concerns. Now, the text of an outgoing text message is immediately evaluated using sentiment analysis and discarded directly afterward. Even more important than the choice of sensors and additional services was the appropriate aggregation of sensor data. For each sensor, we used multiple aggregation functions (e.g., minimum and maximum value, average value, and a normalized number of events) to extract valuable information from the data stream. The high R^2 (0.41) of the stress assessment model involving sensor data showed that the design is suitable for stress assessment. Data analysis further revealed that initializing data processing with a general model built on all users' data can prevent cold-start problems. However, some use cases will use MSA systems over a long period. In these cases, personalization could significantly improve the assessment's performance.

Prototype 2 – Mobile Personalization of Stress Assessment

Application Scenario: We build upon the previous study and aim to enhance the stress assessment model by applying machine learning techniques for personalization purposes. The basis for this addition is Prototype 1, targeting the assessment of perceived stress. Although sensor data collection is also integrated into the user's life, effective personalization requires dropping the requirement of life integration. This necessity is due to model personalization requiring regular user feedback on its prediction performance. More details on this study can be found in Gimpel et al. (2019a).

Design & Development: We extended Prototype 1 and included a feedback system enabling the user to value model performance and the actual stress perception level. Like the initial prototype, Prototype 2 runs on the Android platform and performs data collection, storage, processing, model building, and personalization directly on the smartphone. This focus on smartphone processing brings a substantial limitation of the available resources compared to cloud or desktop processing. The prototype uses sensory data from the user's environment and behavior to determine perceived stress and continually adapts to the user via stochastic gradient descent machine learning. As the prototype expands on Prototype 1, it addresses the same design features.

Empirical Study: We tested the personalization algorithm with 10 participants, each providing 20 or more observations. Compared to stress prediction with the unpersonalized stress assessment model developed within the evaluation of Prototype 1, we could observe a significant improvement of prediction results for all users. However, we found that no fixed learning rate works for all users, and some users are more sensitive to small changes in sensor data than others. This finding supports the claim that stress is highly individual, and each user perceives stress differently. Instead, we use the adaptive learning rate algorithm Adadelta (Zeiler 2012) to acknowledge individual differences.

Learnings: This episode's lessons further substantiate the findings from previous episodes, for example, the importance of resource efficiency for user acceptance. Compared to using a desktop computer for calculation purposes, a smartphone has very scarce resources regarding battery capacity, computing power, or simulation tools. This resource scarcity puts high demands on the quality and efficiency of the personalization algorithm. This episode also provides interesting implications for MSA systems applying machine learning techniques. As data arrives over time, the personalization should apply an online learning algorithm learning one data point at a time, for example, stochastic gradient descent. As a central requirement of our use case, personalization should integrate passively into the user's life and abort when the assessments are sufficiently good. However, the term "sufficiently good" needs clarification, for example, in the form of termination criteria defining success and failure of personalization and terminate personalization accordingly (concerning the robustness dimension of requirements). Finally, a general model might be helpful to avoid cold start problems. However, the same stress assessment model will probably not stay valid forever and eventually require readjustment to maintain assessment accuracy. Therefore, resumption of personalization should be considered using criteria that specify cases in which this readjustment should be triggered.

Prototype 3 – Assessment of Biological Stress using Video Processing

Application Scenario: We built a prototype that continuously assesses an individual's stress level by assessing variations in the user's pupil dilation using video processing techniques. Pupil dilation is a physiological measure, which reflects cognitive load as an indicator for acute stress based on biological body reactions (Andreassi 2010, p. 289 ff; Gao et al. 2007; Winn et al. 1994). This approach can be performed without the user's direct interaction or attention and, thus, be used in everyday life.

Design & Development: We developed a prototype for desktop computers building on the C++ programming language and OpenCV (OpenCV 2016c) computer vision library. It can assess variations in pupil dilation without prior calibration or human intervention. Image processing techniques segment the pupil from the iris. The algorithm calculates the pupil/iris ratio of both eyes, averages them to a single value, and evaluates the segmentation result to assess cognitive load as a stress indicator. Prototype 3 implements the design features as follows: It collects data on biological symptoms (DF1) to assess stress integrated into the user's life (DF2) continuously (DF3). As an outcome, it provides a binary indication for stress (DF4) using a single device (DF5) and raw personal data (DF6), which is discarded immediately after use.

Experimental Setup: We applied the prototype under controlled conditions in a laboratory experiment with 23 participants. Of these participants, six wore glasses, and all eye colors from blue and green to brown were represented. We controlled for confounding variables affecting pupil dilation, such as room lighting. In the experiment, we induced acute stress in the participants with a stress game, which puts participants under stress by creating different stimuli (Schaaff and Adam 2013). While the participants played this game, we video-recorded their faces. Based on this video stream, the prototype analyzed the pupil diameter changes to detect acute stress. As a performance measure, we assessed physiological stress using heart rate variability (HRV) as a biological marker. We pre-processed video, stress game, and physiological data, synchronized them, and segmented them into intervals of one second. We discarded video data not meeting our quality requirements. Our data analysis yields a correlation of 0.471 between pupil dilation and physiological stress as assessed by HRV.

Learnings: We conclude from these results that the assessment of biological stress and the application of video-based sensors are feasible. The development process unveils further important learnings: For biological stress, most physiological markers such as pupil dilation can only be observed with a delay. Simultaneously, physiological markers vary regarding their recovery time, in which the marker returns to the base level. Hence, not every marker might be suitable to detect acute or chronic stress. Finally, raw data is noisy in general. Especially in use cases with low fault tolerance, proper pre-processing is critical.

Prototype 4 – Sensor Fusion for Sleep Duration Assessment as Stress-Related Variable

Application Scenario: As a contrast to the previous prototypes, we do not target the direct assessment of stress with Prototype 4 but build a sleep sensor using sensor fusion techniques as an indicator of stress. The exact role of sleep regarding stress is not clear. However, research has shown that it can affect physical changes, such as muscle repair, mental tasks, and concentration, and cause sleep deprivation (Minkel et al. 2012).

Design & Development: With an Android application, we combine different sensors to assess sleep duration and sleep quality as important stress indicators. Prototype 4 collects primarily environmental parameters from standard smartphone sensors and does not require the user to change their sleeping routines or habits. The basic idea is that the user does not have to explicitly activate a sleep mode, take a specific sleeping position, or position the smartphone on the bed in a certain way. We designed the prototype to recognize the user’s daily routines over time by combining different sensors and mixed stress correlates (DF1). Besides the time of the day, which is a rather obvious indicator of sleeping behavior for most people, sleep prediction can benefit from environmental information such as the current location, illuminance, and ambient temperature. Behavioral signs might include activating the airplane mode charging the smartphone. The prototype also targets life-integrated (DF2) and continuous (DF3) assessment of stress on a binary scale (DF4) and a single device (DF5) and uses, amongst others, raw personal data (DF6).

Empirical Study: We applied the prototype in a field study with nine participants providing data daily for 18 days on average (min: 16, max: 33). Thereby, we collected a total of 30.000 data points. For model building purposes, the prototype uploads data to a cloud. We tested different aggregation and data analytics methods for model building. Again, we needed to remove outliers because of noisy data generated by the smartphone sensors. In our data analysis, a random forest model achieved the best accuracy of 93.23%.

Learnings: In this prototype, we learned another time that resource efficiency is of high importance. However, this prototype also reveals interesting insights into the processing of data: When multiple sensors (e.g., Wi-Fi and cellular) point to the same real-world feature (i.e., the location), it is best to use an aggregation of both values (e.g., the average) to achieve increased robustness. Further, some sensors need time to calibrate. Thus, the first observations have substantially higher measurement error and should be discarded. Sleeping and waking states do not alter too often. Thus, one should consider timely interdependencies between predicted values in the model.

Prototype 5 – Framework for Automated Data Collection, Storage, and Pre-Processing

Application Scenario: Data collection, storage, and pre-processing are essential success factors of stress assessment. Therefore, Prototype 5 aims at building a supportive framework taking care of these three steps. We used a binary classification model for evaluation purposes, distinguishing the states "stressed" and "not stressed." More details on this study can be found in Beckmann et al. (2017).

Design & Development: The framework works as a module providing the functionality needed to efficiently collect data and fuse multiple sensors. A Java package and a port to the Android platform are exemplary instantiations of this prototype and enable use on both stationary and mobile devices. The instantiations use various sensors building on multiple platforms, save data on different databases, and constitute a linking element between numerous components of the design blueprint presented in section 4.1 of our article. As Prototype 5 describes a sensing framework, it can be used for multiple purposes, enabling several design features. In our exemplary study, we use it to collect mixed (DF1) non-personal and aggregated personal data (DF6) in an unobtrusive manner (DF2) to continuously (DF3) determine stress on a binary scale (DF4) running on multiple platforms (DF5).

Experimental Setup: We evaluated the framework with 15 participants, who played the stress-inducing game (cf. Prototype 2) with an additional wearable self-tracking device. The framework collects, stores, and pre-processes data from the mouse, keyboard, and wearable device during the game. To expand the input data, we combined data from different sensors to new, more complex indicators. This approach is commonly referred to as "sensor fusion."

Based on this expanded dataset, we trained a binary classification model. The prediction of stress-free states achieves an accuracy of about 99%, whereas stress states can be predicted with an accuracy of approximately 70%.

Learnings: An important learning from this prototype is that the application of sensor fusion is a very promising approach and can significantly boost small datasets. We achieved very good results in determining stress on a binary scale. As maultiple devices were involved in our experiment, our study demonstrated that sensor fusion is even possible across device boundaries when the same standardized data collection framework is used on all devices.