Toward Better Allergy Management in the Digital Era: Empirical Essays

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Per aspera ad astra***

List of contributions

This doctoral thesis contains the following contributions published in or submitted to scientific journals. The specified categories relate to the journal ranking system #VHB-JOURQUAL3 of the Verband der Hochschullehrer für Betriebswirtschaft e.V. (2015)#. The order of the contributions corresponds to the chronology of publication.

Contribution 1:

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Forecasting tomorrow's Betula and Poaceae airborne pollen concentrations on a 3-hourly resolution in Augsburg, Germany: towards automatically generated, real-time predictions.

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1. Introduction

1.1 Pollen-induced allergies as a public health concern

Atopic disorders triggered by airborne pollen, also known as hay fever, currently impact a large share of the global population with the trends indicating a steady increase (Ring et al. 2012, Traidl-Hoffmann 2017). The prevalence of hay fever, being the most common manifestation of atopic disorders, stagnates on a high level, ranging from 15% to 25% worldwide, with industrialized countries being strongly affected by this negative trend (Passali et al. 2018). Considering specifically Germany, about 30% of the total population suffers from at least one atopic disease (Langen et al. 2013). The prevalence of hay fever amounts to almost 15% of adult population (Bergmann et al. 2016) and about 12.6% of German children (Schmitz et al. 2014). According to the World Allergy Organization, environmental factors such as increasing anthropogenic pollution and urbanization of rural areas might be responsible for high numbers of sensitization (Pawankar 2014). Additionally, gross changes in the environments where we live toward global warming, stimulate plants to pollinate earlier within the year, for a longer duration and more intensively overall in absolute terms (D'Amato et al. 2015, Pawankar et al. 2014). Considering the current development in terms of climate change and progressing urbanization worldwide, an even bigger increase in both, the prevalence of atopic disorders, and exposure of sensitized individuals to airborne pollen should be expected (Damialis et al. 2019).

Hay fever is a disease induced by airborne pollen grains causing an overreaction of the immune system in sensitized individuals (Sofiev et al. 2013). That’s why pollen, originally completely harmless toward human health, are now considered an important component of the so-called biological weather. Allergic symptoms occur seasonally every year and are strongly related to the concentration of pollen grains of allergologicaly relevant species in the ambient air and normally last for several weeks (Karatzas et al. 2014). Although hay fever is often considered a non-life-threatening health condition, it is capable of dramatically altering an individual’s quality of life (Ring et al. 2014).

Allergic symptoms are capable of substantially impairing everyday activities, and social life of allergic individuals (Jernelöv et al. 2013; Blaiss et al. 2018). Additionally, hay fever can reduce workplace and classroom productivity due to the cognitive disturbance caused by allergic symptoms (Bensnes 2016, Marcotte 2015). Occurring allergic symptoms also negatively influence the psychological well-being and perceived quality of life (Devillier et al. 2016; Haanpää et al. 2018; Valls-Mateus et al. 2017) of people concerned. Not willing to be labelled chronically ill, allergic individuals often present their allergic symptoms as caused by a cold or influenza, in order to avoid additional attention and social embarrassment (Cvetkovski et al. 2018). Additionally, hay fever represents a growing public health problem (Schoenwetter et al. 2004). A systematic review of the economic consequences of allergic diseases came to a conclusion, that the majority of economic burden caused by allergic symptoms was indirectly elicited by high levels of reduced productivity in individuals allergic to pollen (Linneberg et al. 2016). Indeed, the overall economic impact of allergic disease accounts for nearly 36% of impaired work productivity and almost 4% missed work time (Vandenplas et al. 2018), and is dependent from the severity of the symptoms (Schramm et al. 2003).

1.2 Allergy management

Since any allergy is a chronic health condition, it requires long-term therapy. Proper and timely initiated allergy management measures can relieve the symptoms and reduce the negative implication of this disease. Taking daily medicine doses or implementing supportive behavior into daily routines do not need constant supervision by medical personnel, and, thus, allergies can be managed outside of healthcare institutions in the long run. Consequently, allergic individuals have to self-administrate their allergy management and are responsible for their own well-being during the pollen season.

There are three main possibilities to manage allergic symptoms: Allergen avoidance, symptomatic pharmacotherapy and specific immunotherapy (May and Dolen 2017). Allergen avoidance, being a systematic avoidance of exposure to airborne pollen, is the most effective measure in allergy management, since the total absence of the allergic reaction-inducing factor, eliminates the immune response of the body (Seedat 2013). Allergen avoidance makes sense only if performed as needed, when concentration of airborne allergenic pollen is high. Nevertheless, allergenic pollen is nearly omnipresent and invisible to human eye. Thus, pollen exposure is difficult to avoid completely, especially during the main pollen season.

Oral antihistamines remain the most frequently used anti-allergy measure (Caillaud et al. 2014). However, it is not to oversee, that a significant share of allergic individuals continue to experience bothersome allergic symptoms, despite the intake of anti-allergic medicine (Hellings et al. 2013, Jaruvongvanich et al. 2016). The absence of expected symptom relief might be associated with loss of faith in traditional treatment methods along with reluctance towards medical assistance, as the healthcare provider is no longer perceived as a competent contact person (Moreau et al. 2012). Disappointment with medical treatment might also result in change to over-the-counter medicine (Lombardi et al. 2015, Tan et al. 2017) or generally poor treatment adherence.

The singly available causal treatment of the hay fever is specific immunotherapy. This treatment method can lead to a life-long tolerance against allergens due to restoration of normal immunity (Akdis et al. 2006), with a clear improvement in disease-specific and general well-being in comparison to only symptomatic treatment (Horn et al. 2016). The allergen immunotherapy can be undertaken exclusively under medical supervision, which makes it cost-intensive for the healthcare system, and time-consuming for allergic individuals. Despite high direct costs, allergen immuntherapy displays a favourable cost-benefit ratio, reducing healthcare costs in the long run (Hankin et al. 2013, Incorvaia 2012). However, this treatment method is not effective in all cases, not least, depending on the pollen species an allergic individual is sensitized to (Meadows et al. 2013).

1.3 Health behavior of allergic individuals

“Drugs don’t work in patients who don’t take them.” This statement made by the former US Surgeon General C. Everett Coop in 1985 is true nowadays as well. The efficiency of every pharmacological treatment or supporting health behavior is limited by the patient’s cooperation (Brown and Bussell 2011). This is especially true for treatments that require self-administration and are performed outside of healthcare institutions, such as allergy management. One the one hand, it is challenging to define the term “nonadherence” in context of allergy management, since many anti-allergic medications are symptomatic and have to be taken as needed (Seedat 2013) and allergen avoidance strategies make sense only if performed at the moment, when airborne pollen concentration is high. On the other hand, anti-allergy measures actually undertaken, and being in line with medical recommendations, might be considered as desirable health behavior of allergic individuals.

To be effective, interventions focusing on improvement of health behavior of allergic individuals, should address the root causes of incorrect health behavior. It is known, that most noncompliance is intentional, implying patient’s voluntary decision not to behave in a healthy way, and might be justified by some considerations or beliefs (Bender 2015). Obviously, the desirable endpoint of the allergy management efforts undertaken by an allergic individual, is improvement and maintenance of his or her health-related quality of life during pollen season. As highlighted in the previous section, there is no treatment or anti-allergic measure, which guarantees the elimination of or relief from allergic symptoms, making a decision for or against some particular anti-allergic measure not obvious. Furthermore, allergic individuals are a heterogeneous group having different expectations regarding desirable benefit from allergy management in terms of promptness and extent of the symptom relief (Cvetkovski et al. 2018). For instance, perceived symptom relief might be seen as not sufficient if not experienced immediately (Ocak et al. 2017). Still, over one out of four allergic individuals do not treat allergy despite persistent allergic symptoms (Spinozzi et al. 2016). Therefore, improving individuals' health behavior must involve focusing on at least some of the hindering silent beliefs. That presumes that the causes of inappropriate health behavior are known. However, information about the reasons of inappropriate health behavior of allergic individuals remains scarce.

1.4 Pollen information

The most allergic individuals take health related decisions regarding their allergy management on their own. It stands to reason, that providing allergic individuals with information, which can be used as a basis for rational decision-making, is of paramount importance, empowering them to undertake meaningful efforts toward proper allergy management. The chronic course of hay fever is in this context an advantage, as it allows allergic individuals to recognize symptom patterns, identify triggers and develop useful strategies in allergy management, which makes allergic individuals capable of taking a larger share of responsibility in symptom management (Cvetkovski et al. 2018). The experience of allergic individuals with allergy management can be used as a valuable resource, since patients engaged in decision-making report higher satisfaction and improved adherence (Bender, 2015).

This reasoning raises the question, how allergic individuals can be effectively supported in their allergy management. It is well-known that severity of the allergic symptoms is associated with the amount of pollen the allergic individual is exposed to (Sofiev and Bergmann 2013). Depending on the phenological and meteorological factors, airborne pollen concentration shows considerable fluctuation in its amount during the main pollen season, causing allergic reactions of various severity. Information on current pollen load, as well as, short-term forecast of expected pollen exposure might be an essential help for allergic individuals when planning their day to day allergy management. As already outlined by Kmenta et al. (2014), pollen information provided to the target population of the allergic individuals, for example via a pollen application, might become an important aid in avoiding exposure to allergenic pollen, as well as planning medication and outdoor activities. Pollen information might empower allergic individuals to make rational, well-informed decisions about their health behavior, with respect to current biological weather.

1.5 Automatic pollen monitoring

Airborne pollen of allergenic species is a recognized indicator of biological weather. Thus, a network of nearly 400 Hirst-type pollen traps is currently monitoring the airborne pollen in Europe with 43 of them being operated in Germany (Berger et al. 2013). Pollen information provided by a Hirst-type volumetric trap has to be assessed manually by aerobiology experts, after it is divided into a number of segments depending on the resolution of desired data. This implies two points: Firstly, the collection of data on current pollen concentration is a time-intensive and error prone process, and secondly, announcement of risk alerts to the public takes place with a delay of at least 8 days. Therefore, a more rapid, and preferably instantaneous technique in pollen monitoring than a conventional Hirst-type pollen trap is needed. In order to address this need, Bavaria is currently developing a network based on the automatic pollen monitoring devices of type BAA500 (Bio Aerosol Analyzer 500) (Oteros et al. 2019). One of this innovative pollen monitoring devices has been in operation at UNIKA-T in Augsburg for half of a decade. The BAA 500 has proven to be a functional pollen counter: 93.3% of pollen reported by this device was recognized correctly with pollen information available three hours after the observation (Oteros et al. 2015). Furthermore, automatic pollen monitoring features the high sampling rate of up to 8 pollen measurements per day, allowing to go beyond the daily pollen values prevalent in current scientific literature (Crouzy et al. 2016). Therefore, automatic pollen tracking is a promising tool in pollen season monitoring, as it provides nearly up-to-date pollen information with a high hourly resolution, and minimizes errors related to manual work.

Providing accurate information on airborne levels of pollen several days ahead to allergic individuals enables them to take preventive anti-allergy measures. The BAA500 allows to provide pollen information for multiple periods within the day, potentially raising the efficacy of anti-allergic measures, as they may be planned in accordance with biological weather. Forecasting of airborne pollen levels has become an important objective in aerobiology and, therefore, there is a significant body of research dedicated to the development of predictive models of airborne pollen concentrations of various allergenic species. However, forecasting of pollen exposure on a hourly scale has not been well represented in research so far.

1.6 Mobile health in allergy management

The next question arising in the context of pollen monitoring is - how, or by which communication channels, should pollen information be disseminated in order to reach the widest possible audience of allergic individuals? Increased availability of health-related information online, coming along with ubiquity of internet access, changes the traditional way of things. Increasingly many people consider internet as an important medium for health purposes (Lausen et al. 2008). Especially health-related mobile apps appear to be a frequently used source of health-related information (Baldwin et al. 2017), as they provide access to healthcare are services anytime and anywhere. Indeed, a rapid growth of popularity of mobile applications designed for chronic disease management was recorded in the last decade (Patrick et al. 2008). These tendencies demonstrate that mobile health services might represent a promising technology, as they address the challenge of the rising number of chronic diseases related to lifestyle or dependent from environmental conditions, like hay fever. Particularly, allergic individuals consuming pollen information reported to be able to better control their health-related well-being (Krebs and Duncan 2015). Furthermore, a strong association between pollen information consumption and actual concentration of allergenic pollen in the air was detected (Kmenta et al. 2016).

Nowadays, there are several pollen applications available on the German market. However, little is still known about the population of allergic individuals consuming pollen information in general, and utilizing pollen applications in particular. Especially the factors motivating sustained pollen application use are of interest, since this information is crucial for popularization of this mobile health solution.

With regard to the highlighted points, the main objective of the present doctoral dissertation is to close research gaps related to allergy management. Inconvenience caused by allergic symptoms is the starting point of all efforts allergic individuals direct toward allergy management. Based mostly on multi-annual experience in allergy management, allergic individuals develop different attitudes and salient beliefs regarding their health state and strategies to control allergic symptoms, which influence their health behavior. Pollen information provided to allergic individuals via pollen applications might become an important pillar in allergy management as it allows to plan anti-allergy measures in advance. However, pollen applications have to be accepted by allergic individuals first. In order to provide pollen information in advance and for multiple periods within a day, accurate predictive models of airborne pollen concentrations based on sub-daily data resolution are needed. With regard to these considerations, the following research questions are of interest:

(1) What are the implications of allergic symptoms on everyday life of allergic individuals?
(2) Which allergy management measures are utilized by allergic individuals?
(3) Which factors facilitate or hinder the utilization of different allergy management measures?
(4) Which factors facilitate the acceptance and utilization of mobile applications providing pollen information?
(5) Which mathematical techniques perform best in predicting airborne pollen levels based on a three-hourly scale of pollen data?

The doctoral thesis contains four contributions to scientific literature to answer the research questions raised above. Contribution 1 examines the current situation regarding the impairment caused by allergic symptoms and highlights frequently performed health behavior of allergic individuals (see research question (1), (2)). Contribution 2 investigates the influencing factors explaining the health behavior of allergic individuals (see research question (2), (3)). Contribution 3 focuses on influencing factors facilitating the acceptance and utilization of pollen applications as a supporting tool in allergy management (see research question (4)). Contribution 4 is devoted to development of predictive models of airborne pollen concentrations on a sub-daily scales of pollen data using time series analysis and machine learning techniques (see research question (5)).

The remainder of this work is structured as follows: Section 2 summarizes four contributions included in this doctoral thesis. Section 3 discusses the contributions in the light of research questions. The section 4 concludes and highlights opportunities for future research and points out major limitations of the presented contributions. In the section 5, the contributions are presented in their full version.

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2. Summaries of the contributions

This doctoral thesis provides several contributions to current research state, which are summarized in this section. The outlines of the summaries reflect ones of the original papers. Please find full version of the contributions in the sections 5.

1 Contribution 1: Pollen allergy and health behavior: patients trivializing their disease

Exploration of the implications caused by allergic symptoms, as well as routine health-related habits of allergic individuals is a reasonable starting point of scientific efforts directed toward improwement of allergy management. For this purpose, Muzalyova et al. have conducted an explorative cross-sectional study focusing on multiple aspects of allergy management. This contribution has been published in *Aerobiologia*, which is not ranked in the VHB-JOURQUAL3 ranking system (Verband der Hochschullehrer für Betriebswirtschaft e.V., 2015). It can be found in its entirety in section 5.1 of this thesis.

As this contribution traces the explorative goal, research questions raised in this scientific work cover a broad spectrum of various aspects of allergy management. In particular, the main body of the paper provides information on the impairment of health-related quality of life caused by allergic symptoms, utilization rates of different allergy management options, and several salient beliefs shared by the examined population. A total of 679 allergic individuals from Germany has participated in the cross-sectional study. The main findings of this contribution can be summarized as following:

(1) Hay fever remains a serious health related problem due to substantial impairment in everyday life caused by its symptoms and is associated with significant loss of workplace and/or classroom productivity.

(2) Despite perceived symptoms, a considerably small proportion of the allergic individuals seek medical support or undergo specific immunotherapy.

(3) The biggest share of allergic individuals self-manages allergic symptoms using over-the-counter medication.

(4) Allergen avoidance strategies as well as pollen information services are moderately used by allergic individuals.

(5) Allergic individuals commonly justify their health-related decisions regarding allergy management by perceived severity of the symptoms.

(6) High state of knowledge about pollen allergy facilitates the utilization of anti-allergic measures.

Conclusion. The presented explorative study gives an overview of current utilization rates of various allergy management measures and provides some insights in reasons, which might be responsible for the stated health behavior. Thereby, the explorative study allows to identify promising research directions. Based on its findings, it appears reasonable to focus on trivialization of hay fever by allergic individuals as the main contributing factors of the poor allergy management.

2 Contribution 2: Determinants of the utilization of allergy management measures among pollen allergy sufferers: A theory based cross-sectional study

In contribution 2, Muzalyova and Brunner (2020) investigate the determinants of the health-related behavior regarding utilization of various allergy management measures using the Protection Motivation Theory. In particular, the main body of the paper provides theoretical background of the conceptual model, information on questionnaire development and main findings obtained in the course of data analysis. This contribution was submitted to BMC Public Health which is not ranked in the VHB-JOURQUAL3 ranking system (Verband der Hochschullehrer für Betriebswirtschaft e.V., 2015). It can be found in its entirety in section 5.2 of this thesis.

Research model. Theories and models of health behavior are helpful for predicting and explaining health behavior in different health related settings. Muzalyova and Brunner (2020) focus in the contribution 2 on the Protection Motivation Theory (PMT) (Rogers 1975) as being the most suitable for the given research context. The PMT incorporates two appraisal processes involved in decision-making regarding health behavior, namely assessment of the threat caused by a disease and evaluation of response strategies aiming at reducing that threat. According to the PMT, the threat appraisal is posed by its perceived *seriousness* and *symptom severity*, referring to the trivialization of hay fever by allergic individuals discovered in the contribution 1. Response appraisal encompassing the evaluation of *response efficacy*, *response costs*, and *self-efficacy* indirectly reflects the experience and knowledge of allergic individuals regarding their longstanding atopic disease. The Transtheoretical Model (TTM) (Prochaska and Velicer 1997), being a multi-stage model of behavior change, was chosen to capture the utilization of the various allergy management measures in order to give a more detailed and comprehensive differentiation between actors and non-actors regarding health behavior of allergic individuals.

Hypotheses tested in the course of empirical investigation were formulated using the PMT paradigm as follows:

H1: Perceived seriousness of allergy positively affects the utilization of allergy management measures.

H2: Perceived severity of allergic symptoms positively affects the utilization of allergy management measures.

H3: Perceived response efficacy of allergy management measures positively affects the utilization of allergy management measures.

H4: Perceived response costs of allergy management measures negatively affect utilization of allergy management measures.

H5: Perceived self-efficacy of allergy management measures positively affects the utilization of pollen allergy management.

Operationalization of the theoretical constructs. The five latent constructs incorporated in the research model, such as perceived *seriousness* of disease allergy, perceived *symptom severity*, and perceived *response efficacy*, *response costs* and perceived *self-efficacy* were operationalized in course of pilot semi-structural interviews with a sample from the target population followed by a pre-test. The stage progress across the TTM stages was operationalized as five answer options according to the five stages of behavior change defined by the TTM, such as *precontemplation*, *contemplation*, *preparation*, *action* and *maintenance*. In total, utilization of five possible allergy management measures was captured in the present empirical study, namely *medical supervision*, *self-responsible allergy management*, *anti-allergic medication*, *specific immunotherapy*, and *allergen avoidance*. The proposed hypotheses were tested based on a cross-sectional study with a sample of 569 allergic individuals.

Summary of the main findings.

(1) Perceived *seriousness* of disease allergy positively affected the utilization of *medical supervision*, and had a tendency to be negatively associated the utilization of *allergen avoidance* strategies (*H1*).

(2) Perceived *severity* of allergic symptoms positively affected the utilization of *medical supervision*, *self-responsible allergy management, anti-allergic medication,* and *allergen avoidance strategies* (*H2*).

(3) *Response efficacy* did not significantly affect utilization of any examined allergy management measures (*H3*).

(4) *Response costs* did not significantly affect utilization of any examined allergy management measures (*H4*).

(5) *Self-efficacy* positively affected the utilization of *medical supervision, anti-allergic medication* and had a tendency to negatively affect *allergen avoidance* strategies (*H5*).

(6) *Specific immunotherapy* was motivated by none of the rational reasons defined by the PMT, but singly by *medical supervision*.
(7) Utilization of *medical supervision* significantly reduced the likelihood to undertake additional measures of *self-responsible allergy management*.

Conclusion. Health-related decisions regarding utilization of various hay fever management measures are substantially stronger motivated by the threat appraisal than by the response appraisal. Self-efficacy is the only significant influencing factor of the response appraisal affecting the allergy management decision. Thus, educational interventions raising the awareness of health risks associated with inadequate allergy management accompanied by measures increasing self-efficacy might be beneficial for the promotion of the appropriate allergy management among allergic individuals.

3 Contribution 3: Acceptance of pollen applications in allergy management: An empirical investigation of influencing factors

Muzalyova (2020) investigated motivational factors facilitating the acceptance and utilization of pollen applications by allergic individuals. In particular, the main body of the paper provides introduction of the conceptual research model, description of the study design and summary of the main findings obtained in the data analysis. This contribution was submitted to the Journal of Information Technology which is ranked in the VHB-JOURQUAL3 ranking system (Verband der Hochschullehrer für Betriebswirtschaft e.V., 2015) in Category B. It can be found in its entirety in section 5.3 of this thesis.

Research model. Mobile health solutions like pollen applications might represent a useful supporting tool in allergy management. However, pollen applications have to be accepted by the target population of allergic individuals first. Technology Acceptance Model (TAM) (Davis 1985) is one of the most influential theories dedicated to explaining the adaption behavior of new technologies. Originally, the TAM was developed for explaining the acceptance of new technologies in workplace settings. However, the TAM was successfully transferred into health-related context. The TAM poses two main influencing variables, namely perceived *usefulness* and perceived *ease of use* to affect *attitude* toward a technology, which in turn affects *behavioral intention* of its actual utilization. According to the current research state following hypothesis were stated:

H1: Perceived usefulness of a pollen application positively affects attitude toward its use.
H2: Perceived usefulness of a pollen application positively affects behavioral intention towards its use.
H3: Perceived ease of use of a pollen application positively affects its perceived usefulness.

H4: Perceived ease of use of a pollen application positively affects attitude toward its use.

H5: Attitude toward a pollen application facilitates behavioral intention toward its use.

Since the endpoint of pollen application use is promotion and maintenance of the health-related well-being, it can be considered a special case of health behavior. Therefore, an additional consideration of a health behavior model is a meaningful extension of the TAM, which will strengthen the conceptual research model. According to this reasoning, the PMT was incorporated in the research paradigm. As the *usefulness* aspects of a pollen application related to the *response efficacy*, and the *ease of use* corresponding to *response costs* are captured by the TAM, only three remaining PMT construct were included in the conceptual model. In line with current state of research, following hypothesis were formulated:

H6: Perceived severity of allergic symptoms positively affects behavioral intention toward use of a pollen application.

H7: Perceived seriousness of allergy positively affects behavioral intention toward the use of a pollen application.

H8: Perceived self-efficacy positively affects behavioral intention toward the use of a pollen application.

H9: Behavioral intention positively affects the actual utilization of the pollen applications.

Operationalization of the theoretical constructs. The latent constructs incorporated in the research model, namely *usefulness, ease of use, attitude, behavioral intention, seriousness* of allergy*, symptom severity,* and *self-efficacy* were operationalized based on reliable scales validated in previous research, and adjusted according to specifics of disease of interest and pollen applications. The respondents' comprehension of the developed scales was tested using a sample of 15 individuals from the target population. The *utilization* of a pollen applications was captured by one item addressing the TTM stages of behavior change.

Study design. Empirical data was collected in the course of an online experiment consisting of two stages: In the first stage all enrolled allergic individuals received an instruction presenting a fictitious pollen application focusing on providing pollen information. For increased realism, study participants were also presented with several mobile phone screenshots showing planned features and intended design of the pollen application. In the second stage the study participants were asked to participate in an online survey inquiring their assessment of the presented pollen service. The theorized conceptual model was analyzed using covariance-based structural equation modeling technique using a sample of 307 recruited allergic individuals.

Summary of the main findings.

(1) The perceived *usefulness* of the pollen application was significantly affected by perceived *ease of use*, and in turn has positively affected the *attitude* toward the use of a pollen application in allergy management (*H1* and *H3*).

(2) The *behavioral intention* to adopt a pollen application was predetermined by positive *attitude* and perceived *seriousness* of allergy (*H5* and *H7*).

(3) The *utilization* of pollen applications was significantly affected by behavioral intention of its use (*H9*).

(4) Only a small share of allergic individuals questioned in the present study was totally reluctant towards utilization of a pollen application.

(5) The TAM influencing variables had a substantially stronger effect on *behavioral intention* in comparison to the PMT constructs.

Conclusion. Perceived *usefulness* was the strongest influencing variable affecting *behavioral intention* to use a pollen application. Among examined PMT influencing variables, singly perceived *seriousness* was significantly associated with the *behavioral intention.* Therefore, the development of pollen applications should focus in first line on providing high quality health-related content satisfying the needs of the target population taking their disease seriously. According to the presented fictitious pollen application, that implies a supply of pollen information without gaps during the whole pollen season accompanied by pollen forecasting several days ahead.

4 Contribution 4: Forecasting tomorrow's Betula and Poaceae airborne pollen concentrations on a 3-hourly resolution in Augsburg, Germany: towards automatically generated, real-time predictions.

Pollen forecasting has become an important objective in aerobiology, enabling the short- and long-term predictions of airborne pollen concentrations. Providing the accurate information on expected airborne pollen concentrations to allergic individuals might be of a paramount importance, since it enables them to take preventive anti-allergy measures or to plan their outdoor activities. Muzalyova et al. (2020) investigated the capability of different forecasting techniques in predicting airborne pollen concentrations having a three-hourly resolution. In particular, the main body of the paper provides a detailed description of applied forecasting techniques, developed predictive models and results of an independent test. It can be found in its entirety in section 5.4 of this thesis.

Study design. The main objectives of the study were to identify the intra-day variation of airborne pollen concentrations and to develop a short-term predictive model using the data provided by automatic pollen monitor on a three-hourly scale for *Betula* and Poaceae pollen taxa. Apart from autoregressive integrated moving average (ARIMA) and dynamic regression (DR), a neural network autoregression (NNAR) and an artificial neural network (ANN) were employed for development of the predictive models for a one-day-ahead forecast for both examined species. The available dataset comprising pollen data of the years from 2016 to 2019 was divided into training (pollen data 2016, 2017, and 2018) and validation datasets (2019) in order to test the established predictive models in an independent test. Several meteorological variables were incorporated into the predictive models as influencing variables. Performance of the forecasting models was evaluated based on the difference between observed and predicted values using the mean average error (*MAE*), the root mean squared error (*RMSE*) and the coefficient of determination (R^2) as accuracy criteria.

Main findings:

(1) The pollen release of *Betula* was more intensive in absolute terms, peak values and also average pollen concentration per measurement then of that of Poaceae.

(2) *Betula* airborne pollen concentrations were relatively constant during the day with the highest levels occurring in the afternoon, whereas the pollen concentration of Poaceae was noticeably peaking twice a day with relatively low abundance during the night hours.

(3) Air temperature and precipitation had a significant effect on pollen levels of both examined allergenic species with precipitation being substantially stronger influencing variable

(4) Neural network autoregression was superior in predicting *Betula* pollen concentrations achieving the R^2 of 0.62

(5) Seasonal ARIMA was superior in predicting Poaceae pollen levels achieving R^2 of 0.55

Conclusion. The employed mathematical techniques were shown as valuable tools in development of predictive models based on three-hourly scale of pollen data, achieving the coefficient of determination between 0.13 and 0.62 for *Betula*, and R^2 between 0.03 and 0.55 for Poaceae pollen concentrations. Predictive models explicitly considering autoregression in the data and external predictors such as dynamic regression and autoregressive neural network performed clearly better that those using either only autoregression or singly meteorological factors.

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3. Discussion of the contributions

The present thesis incorporates the four contributions presented in the previous section. In the following, the contributions will be discussed in the light of the five research questions laid out in the introduction:

(1) What are the implications of allergic symptoms on everyday life of allergic individuals?
(2) Which allergy management measures are utilized by allergic individuals?
(3) Which factors facilitate or hinder the utilization of different allergy management measures?
(4) Which factors facilitate the acceptance and utilization of mobile applications providing pollen information?
(5) Which mathematical techniques perform best in predicting airborne pollen levels based on a three-hourly scale of pollen data?

Research question (1): What are the implications of allergic symptoms on everyday life of allergic individuals?

The present doctoral thesis focuses on improvement of allergy management by providing pollen information to the target population of allergic individuals. Detailed examination of health-related impairment caused by allergic symptoms, is an apparent starting point, since it helps to assess if, and to which extent, a need for improvement exist. Therefore, the main goal regarding research question (1) is to give a comprehensive overview of the impairments caused by allergic symptoms in people concerned.

The empirical evaluation of the implications of everyday life caused by allergic symptoms shown in contribution 1 sticks to the definition of the health-related quality of life provided by World Health Organization. According to this definition, health-related quality of life is a multidimensional construct representing the state of the complete physical, mental, and social well-being and not merely absence of a disease (Callahan, 1973). This definition respects the fact, that allergic individuals with the same clinical criteria can dramatically differ in perceived impairment of health-related well-being in general, or perceived limitations of everyday life due to their health state. In line with it, different dimensions of potential impairment caused by allergic symptoms, such as limitations in spare time, social life and workplace productivity, sleep quality and psychological well-being, were evaluated empirically and presented in Muzalyova et al. (2019).

Summarizing, contribution 1 confirms that hay fever remains a serious health-related problem with a profound effect on the health-related quality of life of allergic individuals, with negative implications in social life, everyday activities, goodnight sleep and significant decline of work productivity.

Research question (2): Which allergy management measures are utilized by allergic individuals?

Whereas research question (1) focused on the impairment caused by allergic symptoms, research question (2) discovered the health-related behavior aiming to reduce the negative implications of these symptoms. The main goal is to examine different allergy management strategies in terms of their utilization by the target population of allergic individuals.

The objective is achieved by an empirical investigation presented in contribution 1. As allergies are often managed outside of healthcare institutions, and the majority of possible allergy management measures, do not require approval by healthcare specialists, quality of health and consequently quality of life is essentially dependent on health habits of allergic individuals. As improvement of the perceived well-being in allergic individuals within the pollen season can be facilitated by their health behavior, its evaluation is indispensable. The extensive overview of the current utilization rates of various available pollen allergy management measures are given in contribution 1 highlighting an uncovered need for better allergy management. An additional investigation of reasons of the stated health behavior has highlighted promossing research directions aiming in discovering key drivers and inhibitors of the utilization of various allergy management measures.

In summary, despite perceived symptoms, the largest share of allergic individuals was eschewing medical supervision preferring self-reliant allergy management using over-the-counter medication.

Research question (3): Which factors facilitate or hinder the utilization of different allergy management measures?

As research questions (1) and (2) are intended to provide a comprehensive overview of the current situation in allergy management, research question (3) focuses specifically on discovering the main determinants of health behavior.

Assuming health related behavior in allergy management is rationally predetermined by some salient beliefs or considerations, a research paradigm based on the Protection Motivation Theory was established and empirically tested by Muzalyova and Brunner (2020) on a sample of allergic individuals. Findings presented in contribution 1 answering research questions (1) and (2) were used as basis for decision-making in favour of this health behavior model. Potential influencing variables of allergy management were identified as perceived severity of the symptoms and established health habits and routines coming along with multi-annual experience with this disease. Perceived severity of the symptoms correspond to the threat appraisal and allergy experience might be reflected by response appraisal defined by the Protection Motivation Theory.

Summarizing, the threat appraisal, consisting of perceived severity of the symptoms and perceived seriousness of allergy was shown to be the most relevant motivator of allergy management efforts performed by allergic individuals.

Research question (4): Which factors facilitate the acceptance and utilization of mobile applications providing pollen information?

While research questions (2) and (3) focus on the presentation of health behavior currently seen in allergic individuals, research question (4) introduces a pollen application as a potential supporting tool in allergy management and investigates its added value for the target population of allergic individuals. Therefore, the main goal of research question (4) is to identify influencing factors facilitating the acceptance and utilization of mobile applications in order to address the target population by the development of this mobile health solution.

Several allergy management measures make sense if performed in accordance with the current biological weather. For instance, allergen avoidance strategies make sense only if performed when the airborne pollen concentration is high. Thus, pollen information provided to allergic individuals might support decision-making process by enabling them to take preventive allergy management measures or to plan everyday activities. As pollen information and, particularly, pollen applications are rarely used by allergic individuals, it is reasonable to provide a concrete input on appearance and functionality of the intended pollen application before evaluating its utility for the target population. Muzalyova (2020) investigated the acceptance of pollen applications in an online experiment, consisting of a presentation of a fictitious pollen application with its following evaluation by the study participants. The tested research paradigm incorporated the Technology Acceptance Model (TAM) and the Protection Motivation Theory (PMT) due to the fact that the research question was situated at the intersection of two disciplines, namely information systems and healthcare.

Summarizing, the IT-driven factors have substantially greater influence on the acceptance decision of allergic individuals, than allergy characteristics. Therefore, the development of explicitly desirable features can facilitate the acceptance of pollen applications. However, to assure sustained use, pollen applications have to focus on providing high quality health content and pollen information in order to be perceived as a useful supporting tool in allergy management by allergic individuals taking their disease seriously.

Research question (5): Which mathematical techniques perform best in predicting airborne pollen levels based on a 3-hourly scale of pollen data?

Research questions (1) through (4) focus on the examination of allergic individuals' needs and discovering possible ways to cover these needs. Conversely, research question (5) takes a closer look at pollen information to be provided via a pollen application. The main purpose of this research question is to examine the capability of different forecasting techniques in constructing short-term pollen levels prediction based on a three-hourly pollen data.

In order to achieve this goal, four years of pollen data of *Betula* and Poaceae allergenic species provided by automatic pollen monitoring were used to develop and test predictive models using four different data modelling techniques. Apart from seasonal autoregressive moving average model (ARIMA) and dynamic regression, neural network autoregression, and artificial neural network were employed for the development of the predictive models on the training dataset and tested on the validation dataset. The performance of the predictive models was assessed based on error metrics (*MAE* and *RMSE*) and on the coefficient of determination (R^2) achieved by each forecasting model.

In summary, the tested forecasting techniques have shown the ability to recreate most of the variation in the pollen behavior for both examined allergenic species. However, forecasting techniques explicitly using autoregression and considering external meteorological variables were superior in data modelling.

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4. Conclusion

The present cumulative doctoral thesis examines different aspects of health behavior of allergic individuals and potential of pollen applications to become a supporting tool in allergy management. The current scientific work is motivated by increasing number of prevalence of atopic disease among German population coming along with gross changes in the environment toward the global warming. It provides four contributions to literature, which are summarized, presented in full and discussed in the light of five research questions.

Contribution 1 investigates the current situation regarding the impairment of health-related quality of life by allergic symptoms in Germanan population, and gives an overview of utilization rates of different allergy management options, including the utilization of pollen information services. Contribution 2 focuses on explaining the health behavior of allergic individuals using the Protection Motivation Theory. Contribution 3 presents a pollen application as a potential supporting tool in allergy management and investigates the acceptance motivation by the target population of allergic individuals. Finally, contribution 4 focuses on development of predictive models of airborne pollen concentrations using four different forecasting techniques, based on three-hourly pollen data provided by automatic pollen monitoring.

Based on insights provided by the research efforts presented in the doctoral dissertation, several recommendations regarding empowerment of allergic individuals and their support in allergy management were suggested. A possible extension of these scientific findings, is to test the utility of the provided recommendation using experimental and longitudinal study designs. This research questions are especially interesting in context of the third contribution presenting a pollen application as a supporting tool in allergy management. The idea of a study using a functional pollen application opens a large domain of opportunities for further research. Firstly, the utility of pollen applications can be tested in an experimental setting with a control group, helping to understand how regularly consumed pollen information influences health behavior, and which implications does this have on the perceived health-related quality of life. A longitudinal monitoring of study participants may enable to track long-term developments in perceived usefulness of the pollen application, and pollen information in general. Secondly, a pollen application can be used as a medium for educational interventions aiming at empowerment of allergic individuals in allergy management. Thirdly, a pollen application might be a useful tool for collecting the data on the perceived symptom severity and impairment of everyday life. Since there is no defined threshold for pollen levels inducing an allergic reaction of a certain severity (Voukantsis et al., 2013), the symptom information collected in this way might be helpful for linking the observed airborne pollen concentrations to perceived health-related quality of life. This consideration opens a promising extension of contribution 4, focusing on pollen forecasting. Definition and validation of pollen thresholds inducing allergic symptoms of various severity will enable development of predictive models for forecasting of critical values and or allow personalized symptom forecasting based on the well-being data provide by a pollen application user (Voukantsis et al., 2015)

The opportunities for future research implicitly reveal major limitations regarding this doctoral thesis: The present scientific work focuses exclusively on cross-sectional studies without considering longitudinal or experimental study designs enabling to examine the change in opinion or perceived well-being when exposed to different airborne pollen concentrations. Furthermore, as contribution 1 and 2 involve students as study participants representing a convenience sample. It might bring a certain extent of bias in respondents' answers. However, the results may be representative for highly educated, young allergic individuals. Contribution 3 overcomes this problem by using a different recruitment strategy addressing allergic individuals active in self-help groups in social media. Furthermore, the presented scientific works rely on self-reported information provided by study participants regarding their allergy characteristics like sensitization against certain airborne allergens. Therefore, involvement of a professional medical doctor for testing the stated sensitization based on actual medical characteristics is recommended.

The present scientific work has identified an unmet need for better allergy management. The thesis on hand contributes application-oriented aspects of empowerment and support of allergic individuals using modern mobile health technologies. The consideration of the perspective of allergic individuals might help reflect the current situation in allergy management and provide tailored solutions covering urgent needs of allergic individuals.

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5. Contributions to scientific literature

5.1 Contribution 1: Pollen allergy and health behavior: patients trivializing their disease

The contribution has been accepted for publication in "Aerobiologia", which is not ranked in the VHB-JOURQUAL3 ranking.

Muzalyova A, Brunner, JO, Traidl-Hoffmann C, Damialis, A (2019): *Aerobiologia* 35 (2), S. 327–341. DOI: 10.1007/s10453-019-09563-5

5.2 Contribution 2: Determinants of the utilization of allergy management measures among pollen allergy sufferers: A theory-based cross-sectional study

The contribution has been accepted for publication in “BMC Public Health”, which is not ranked in the VHB-JOURQUAL3 ranking.

Muzalyova A, Brunner, JO (2020): Determinants of the utilization of allergy management measures among pollen allergy sufferers: a theory-based cross-sectional study. *BMC Public Health* 20:1876. DOI: 10.1186/s12889-020-09959-w

Abstract

Background: The quality of life of chronically ill individuals, such as hay fever sufferers, is significantly dependent on their health behavior. This survey aimed to explain the health-related behavior of allergic individuals using the protection motivation theory (PMT) and the transtheoretical model (TTM).

Methods: The influencing variables stated by PMT were operationalized based on data from semistructured pilot interviews and a pretest with 12 individuals from the target population. The final questionnaire inquired perceived seriousness and severity of hay fever, response efficacy, response costs, self-efficacy, and the use of various hay fever management measures in relation to the TTM stages. Multivariate logistic regression was performed to investigate the relationships between the PMT constructs and the examined health behavior.

Results: A total of 569 allergic individuals completed the online questionnaire. Only 33.26% of allergic individuals were in the maintenance stage for treatment under medical supervision, and almost 60% preferred hay fever self-management. A total of 67.56% had a well-established habit of taking anti-allergic medication, but only 25.31% had undergone specific immunotherapy. Nevertheless, 27.09% were taking the latter into consideration. The likelihood for the medical supervision was positively influenced by perceived severity (OR = 1.57, 95% CI: 1.19-2.07), seriousness (OR = 2.41, 95% CI: 1.56-2.94), and also self-efficacy (OR = 3.75, 95% CI: 2.36-5.97). The severity of the symptoms has predetermined the self-responsible hay fever management (OR = 1.60, 95% CI: 1.21-2.11), as well as the anti-allergic medication intake (OR = 1.60, 95% CI: 1.13-2.26). The latter measure was also positively influenced by self-efficacy (OR = 2.41, 95% CI: 1.38-4.19) and hay fever self-management (OR = 4.61, 95% CI: 2.76-7.78). Undergoing specific immunotherapy was significantly predetermined only by medical supervision (OR = 11.17, 95% CI: 6.81 18.30). Allergen avoidance was a strategy used by allergic individuals who preferred hay fever self-management (OR = 2.43, 95% CI: 1.56-3.80) and experienced notable symptom severity (OR = 2.11, 95% CI: 1.59-2.79).

Conclusion: Educational interventions that increase the awareness of health risks associated with inadequate hay fever management and measures to increase self-efficacy might be beneficial for the promotion of appropriate hay fever management among allergic individuals.

Keywords: hay fever management, utilization of health measures, protection motivation theory, transtheoretical model, threat appraisal

1. Introduction

Quality of health and quality of life are essentially dependent on an individual's lifestyle and health habits. By managing their health behavior, individuals can significantly improve their well-being and live longer and healthier lives. This consideration is especially important for individuals suffering from chronic health conditions, which significantly influence their health-related quality of life. Allergic rhinitis, also called hay fever, is considered by the World Allergy Organization to be one of the most prevalent chronic diseases of the respiratory tract (Pawankar 2014). In Europe, the prevalence of hay fever stagnates on a high level ranging from 13% to 25% among industrialized countries (Bauchau and Durham 2004) and continues to grow in its prevalence and severity (Meltzer et al. 2009) especially in children (Kusunoki et al. 2009). Hay fever, as a chronic disease, impairs the everyday activities, sleep quality, and workplace productivity of its sufferers (Blaiss et al. 2018; Meltzer et al. 2017; Muñoz-Cano et al. 2018; Devillier et al. 2016a) and lowers their perceived quality of life (Bensnes 2016; Marcotte 2015). Hay fever sufferers have several options to control the severity of allergic symptoms, such as the intake of antihistamines, specific immunotherapy, or allergen avoidance (Scadding 2015). Despite the benefits of allergy management through such practices, approximately 70% of hay fever sufferers do not treat their disease properly (Muzalyova et al. 2019) or fail to meet current allergy management recommendations. Nevertheless, one of four allergic individuals undergoes no treatment despite having symptoms (Spinozzi et al. 2016). Therefore, the question of how hay fever sufferers can be motivated to manage their disease remains a crucial research direction

The scientific community has mostly focused on the supply side of the problem of hay fever and the development of new medications and therapies to be offered to disease sufferers. However, it is reasonable to examine the other side of the problem and shift the research focus on the demand side (Bandura 2004). This approach can help to promote effective self-management and health habits that keep people healthy across their lifespan. In general, theories and models help predict and explain health behavior in various health-related contexts (Heckhausen and Heckhausen 2010; Conner and Norman 2005). The theories and models of health behavior can be classified as motivational, behavioral inaction, and multi-stage models of behavior change (Armitage and Conner 2000). Motivational theories propose continuous models to predict health behavior at a single point in time or identify the influencing factors of health-related behavior. Behavioral inaction theories are intended to close the gap between motivation and actual behavior. Multistage models assume that individual progress through various stages in the execution of the desired behavior that ranges from the intention to engage in the target behavior to the maintenance of the target behavior(Lippke and Renneberg 2010).

Multistage models highlight the dynamic nature of behavior change based on the assumption that individuals at different stages think and behave in qualitatively different ways (Bridle et al. 2005).

Protection Motivation Theory (PMT). Protection motivation theory (PMT) is a prominent example of a motivational theory of health behavior first described by Rogers in 1975 (Rogers 1975). According to this theory, the protection motivation results from an evaluation processes consisting of threat and response appraisal. Threat appraisal posed by a disease consists of two major components: expected symptom severity and expected vulnerability, being the likelihood of the occurrence of this disease. The response appraisal describes the assessment of efficacy or value of certain health behavior in reducing the threat caused by a disease, and consists of three components: response efficacy, response costs, and self-efficacy. Response efficacy measures the expected benefit in preventing the disease or its harmful influence on health and well-being by the target behavior. Response costs comprise expected physical, psychological, financial, and other efforts involved in the target behavior. Self-efficacy describes to which extent an individual feels capable of performing the target behavior (Lippke and Renneberg 2010).

The stronger the perception of the severity of the potential disease and its likelihood of occurrence, the more the individual will be motivated to protect himself from that negative outcome (Tannenbaum et al. 2015). However, the individual has to perceive that the target behavior will provide substantial benefits in preventing the negative health outcome. If the threat caused by a disease is perceived to be strong but there is no effective way to prevent the disease or to weaken its negative influences, the individual might reach for maladaptive responses like avoidance, denial or wishful thinking (Barth and Bengel 2001). Furthermore, if some particular behavior is perceived as too expensive, painful or challenging it might represent a barrier preventing an individual from the adoption of the new behavior. Thus, the utility of response efficacy and self-efficacy has to overweight the response costs of the target behavior (Conner and Norman 2005).

There is a significant body of research using the PMT to describe health behaviour in different health-related contexts including self-reported adherence to corticosteroid medication among asthma patients (Bennett et al. 1998), self-reported adherence to weight loss recommendations (Mirkarimi et al. 2015), self-reported adherence to therapy among people with coronary heart disease and use of alternative medicine (Kristoffersen et al. 2017), promotion of exercise and healthy dietary behavior (Zhang and Cooke 2012), and non-pharmaceutical protective behavior during influenza outbreaks (Timpka et al. 2014).

Meta-analytical studies have shown significant effects of all PMT components on health behavior (Floyd et al. 2000; Milne 2000). According to Floyd et al. (2000), the effect sizes of the components of threat appraisal were in the small to medium range with vulnerability being the strongest predictor of protective behaviour. The effect sizes of the components of the response appraisal were in medium to large range with self-efficacy exerting the strongest effect on the behavioral intention and actual behavior (Floyd et al. 2000). A similar result was obtained by Milne (2000) with threat appraisal effect sizes laying in the small to medium range and the response appraisal components exerting medium to strong effects (Milne 2000). On contrary to Floyd et.al. (2000), the more scrupulous meta-analysis of Milne (2000) has shown the response costs to be the strongest predictor of intention and future behavior, followed by the effect of self- efficacy (Milne 2000).

Transtheoretical Model (TTM). The TTM, first described in 1992 (Prochaska et al. 1992), is one of the most popular multi-stage models of health behavior that proposes an individual to pass through five stages of change regarding some particular behavior. This stages are: Precontemplation – no consideration of behavior change, Contemplation – consideration of behavior change but not decided yet, Preparation – intention to change behavior and preparation for this change, Action – initiation of new behavior where new behavior is performed recently, and Maintenance – well-developed habit to perform the target behavior (Prochaska and Velicer 1997). The TTM assumes, that behavior change is rather a process than a single event with an individual passing through stages as his or her behavior changes from unhealthy to healthy. The stage movement is associated with the change in the individual's perception regarding pros and cons, perceived self-efficacy and some other salient beliefs regarding the target behavior (Prochaska et al. 1992).

Stage based approaches to behavior change have received a widespread scientific approval. There is a significant body of research applying the TTM to examine variety of health behavior contexts including asthma self-management (Krieger et al. 2009), physical activity (Romain et al. 2018), obesity prevention (Lee et al. 2017), sun protection (Yusufov et al. 2016), and smoking cessation (Gökbayrak et al. 2015). In the present study, we focus on the stages of change defined by the TTM exclusively for providing a more detailed and comprehensive differentiation of actors and non-actors concerning the use of different allergy management measures among allergic individuals. The achieved stage progress will be explained by the PMT constructs.

The main research objective of the present study was to explain the health-related behavior of hay fever sufferers based on protection motivation theory, as this theory was considered to be the most suitable for the specific features of hay fever. The stages of behavior change outlined in the TTM were employed in this study to provide a more detailed and comprehensive differentiation of actors and nonactors regarding the use of different allergy management measures among allergic individuals. To our knowledge, neither the PMT nor the TTM has been used in previous research to assess the behavior of allergic individuals regarding their hay fever management. The influencing variables corresponding to the PMT constructs were expected to explain the motivation of allergic individuals to undertake or forego particular health-related measures. Therefore, the research question examined in the present survey was formulated as follows:

How do PMT constructs influence the utilization of different hay fever management measures among allergic individuals?

2. Materials and methods

2.1 Operationalization of the PMT constructs

The operationalization of the PMT constructs was carried out in two stages: pilot semistructured interviews and a pretest with a sample of 12 individuals from the target population. The participants in the preliminary analysis were recruited from a pool of allergic individuals who had participated in our previous research [12]. The interviews aimed to identify the participants' salient perceptions of the health threat caused by hay fever as well as the perceived reasonability and efficacy of the possible health-related measures aimed at reducing allergic symptoms. The main objective of the pretest using draft versions of the PMT scales was to test respondents' comprehension of the scales and determine appropriate wording for the statements.

The interviews consisted of open-ended questions regarding the PMT constructs and closed-ended questions regarding the utilization of various hay fever management measures. Each recruited allergic individual completed a semistructured interview covering topics presented in the following section.

Threat appraisal. Perceived *vulnerability* was operationalized as perceived *seriousness* of hay fever since allergic individuals already had the disease of interest, and thus, it would not be relevant for them to appraise their likelihood of getting hay fever. There are some interesting insights in our previous research suggesting a crucial impact of the perceived *seriousness* of hay fever on its management (Muzalyova et al. 2019) making this adaptation reasonable. Along with the study of Bennett et al. (1998) investigating adherence to preventive asthma medication, in the present study the perceived *seriousness* of hay fever was inquired as to the perceived chronicity of hay fever (Bennett et al. 1998). Also, the inquiries of threat appraisal focused on the perceived need for hay fever treatment and its advantages and disadvantages. The perceived *severity* of hay fever was assessed based on the negative effects of allergic symptoms on various dimensions of everyday life, with a focus on social functioning, school or workplace productivity, and quality of sleep when symptomatic.

Response appraisal. *Response efficacy* was operationalized as the perceived or possible positive effects of known hay fever measures on health-related well-being when symptomatic. The open-ended questions concerning *response efficacy* were designed to address the dimensions that allergic individuals mentioned being negatively affected by allergic symptoms in the previous part of the interview. *Response costs* were estimated as the barriers preventing allergic individuals from taking action or the inconvenience arising from the need to take hay fever management measures consistently and regularly. *Self-efficacy* was assessed by questions regarding the individual's perceived ability to positively influence his or her well-being when symptomatic. Another dimension of *self-efficacy* was the individual's perceived capability of carrying out health-related measures regularly and consistently. Following the interviews, draft versions of the PMT scale were administered to the recruited interviewees. The list of these items was adapted to the specifics of hay fever and handed out to the allergic individuals following the interview.

All items assessing the PMT constructs were drafted as closed-ended questions consisting of belief statements followed by a five-point Likert scale (1 = totally disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 = totally agree). Allergic individuals were asked to assess the applicability of the statements to themselves. Furthermore, we have encouraged study participants to give general feedback on the questionnaire and to indicate items that were not clearly formulated or were difficult to understand. Based on the insights obtained in the interviews, additional items with belief statements that had not been previously considered were added to the original drafts of the PMT scales. The less important beliefs corresponding to each PMT component were excluded from the final questionnaire. Additionally, the wording of some items was changed to be more explicit and easy to understand. Examples of the items of each particular scale can be taken out from Table.

Table1: PMT scales, developed based on the pilot-interviews and the pretest

Scale	Items	Item examples (selection)
Seriousness	6	"Hay fever is a health condition which has to be treated " "Hay fever is a chronical disease"
Severity	6	"My hay fever symptoms decrease my workplace productivity" "Because of my pollen allergy symptoms I feel limited in my everyday life"
Response efficacy	5	"Hay fever management decreases my symptom severity" "Hay fever management helps to control my disease"
Response costs	6	"Hay fever management is time consuming" "Hay fever management negatively affects my everyday life"
Self-efficacy	10	"If necessary, I am able to undertake health measures regularly" "If I take care of myself, I can avoid heavy symptom burden during the pollen season"

2.2 Operationalization of the allergy management across the TTM stages

Allergy management was assessed with five items specifying five possible allergy management measures: treatment under medical supervision, hay fever self-management, anti-allergic medication, specific immunotherapy, and allergen avoidance. The respondents were asked to indicate their current stage in the utilization of each hay fever management measure. The possible answers to the statements, e.g. "I take anti-allergic medication" were "no, and I do not intend to" (pre-contemplation); "no, but I might think about it" (contemplation); "no, but I strongly intend to do so" (preparation); "yes, but I only started doing it recently" (action); and "yes, and I have been doing it for a long time" (maintenance). Therefore, the use of the TTM allowed us to evaluate both intention and action regarding the target behavior.

Based on the insights from the pretest and pilot interviews the final questionnaire consisted of 33 items related to the PMT constructs, five items on hay fever management, and several items inquiring about the allergy characteristics of survey participants.

2.3 Participants and procedure

This cross-sectional study was conducted between the 9th and 30th of September 2019 using an online survey tool. The start date of the study was intentionally chosen to avoid high pollen load and thus to increase the likelihood of study participants being asymptomatic at the time of the study. The study target group was defined as hay fever sufferers who are sensitized exclusively to airborne pollen. Consequently, only participants who were allergic to airborne pollen and did not have additional perennial allergies to dust mites or animal dander were included in the study. All study participants who did not meet the defined inclusion criteria were excluded from the data analysis. The inclusion of the participants in the study was based on self-reported information on pollen sensitization.

The questionnaires were distributed to all participants who were recruited during the previous study conducted in June and July 2016 to collect data on the health behavior of hay fever sufferers. Additionally, we invited all matriculated students of the University of Augsburg as well as all university personnel who were allergic to airborne pollen to participate in the present survey. A total of 805 invited allergic individuals accessed the online questionnaire, and 569 (70.7%) completed it. Eight study participants were excluded since they did not fulfill the inclusion criteria due to an additional sensitization to dust mites (n = 7) or animal dander (n = 1). Consequently, the remaining 561 participants were found eligible, and their responses were used for data analysis.

3. Data analysis

The survey results were analyzed using SPSS 25 (Statistical Package for the Social Sciences; SPSS Inc., Chicago, IL, USA) and AMOS SPSS 25. The majority of eligible study participants (85.56%, n = 480) answered all items, and no item had more than 3.21% (n = 18) missing values. The missing values for the items on PMT components were imputed using SPSS MVA regression with gender, allergy characteristics, and responses to the complete PMT subscale items as predictors. In line with the multiple imputation routines, a total of m = 50 different datasets were imputed to assure the appropriate statistical power of the inferencestatistical analysis of the data (Graham et al. 2003).

The scales of measurement for each PMT construct were tested for reliability (Cronbach's α 0.876 to 0.665) and averaged across items to use in the logistic regression as independent variables. The data were statistically described in terms of mean and standard deviation (SD) for the interval- and ordinal-scaled values, and frequencies (percentage from the total number of cases) for the nominal-scaled data. Frequencies were used to describe the utilization rates of different hay fever management measures as well as the demographics. The dependent variables characterizing the stage progress regarding the utilization of different hay fever management measures were aggregated to dichotomous, categorically scaled variables differentiating between the actors and non-actors of each inquired hay fever management measure. The correlation analysis was carried out using Spearman's rho coefficient due to the missing normal distribution of the data. Multivariate logistic regression was applied to investigate the relationships between the PMT constructs used as independent variables and aggregated stage progress variables used as dependent variables. The stage progress variables describing the utilization of different hay fever management measures were stepwise imputed in the model as independent variables so as to investigate its interdependencies. Statistical significance was considered at the level of 0.95 ($p < 0.05$). To meet the current criticism on frequentistic methods and p-values specifically, we explicitly involved simultaneous tests. Consequently, all p-values given in this paper are adjusted for multiplicity using Benjamini-Yuketieli step-up procedure (Benjamini and Yekutieli 2001).

4. Results

4.1 Descriptive results

Females constituted 61.85% (*n* = 347) of the total study sample. The study participants had exhibited allergic symptoms for 14.59 (SD = 9.80) years. Information on the use of various hay fever management measures is outlined in Table 1. Only 33.16% (*n* = 186) of the study sample was in the maintenance stage for allergy treatment under medical supervision, whereas almost sixty percent (*n* = 333) were in the maintenance stage for allergy self-management. Approximately thirty percent (*n* = 171) claimed that they were not being treated under medical supervision and that they did not intend to do so (pre-contemplation stage). Those who had a well-established habit of taking anti-allergic medication accounted for 67.56% (*n* = 379). Only 25.31% (*n* = 142) of all individuals were in the maintenance stage of specific immunotherapy, but another 4.81% (*n* = 27) were in the action stage, having started it recently. A total of 27.09% (*n* = 152) of the survey participants stated that they were thinking about the possibility of utilizing specific immunotherapy but were not currently undergoing it (contemplation stage). Almost half (*n* = 277) of all participants were in the maintenance stage for allergen avoidance measures, whereas approximately one-fifth had completely stopped practicing this allergy management measure.

Due to a small size resulting in a small number of survey participants at the contemplation and preparation stages, the TTM stage variables were aggregated as dichotomous, categorical variables to differentiate between early-stage and late-stage of action regarding five examined allergy management measures. Following Prochaska et al. (1992), the early-stage included pre-contemplation, contemplation, and preparation stages of behavior change, and the late-stage included action and maintenance (Prochaska et al, 1992). Therefore, participants in the early stages were not utilizing particular hay fever management measures, including those reporting total resignation, contemplation, or intention of a target behavior. Participants in the late stages included allergic individuals who had utilized particular hay fever management measures recently or for a longer time. Consequently, study participants in the two categories can be referred to as *nonactors* and *actors.*

Table 2: Utilization of different allergy management measures expressed as TTM stages (in %)

	Early stage (not taking action)				**Late stage (taking action)**		
	Precontemplation	Contemplation	Preparation	*Σ*	Action	Maintenance	*Σ*
Medical supervision	30.48	22.82	6.42	*59.72*	7.13	33.15	*40.28*
No medical supervision	18.18	7.49	2.50	*28.17*	12.48	59.35	*71.83*
Anti-allergic medication	10.70	7.13	1.43	*19.26*	13.19	67.55	*80.74*
Specific immunotherapy	37.62	27.09	5.17	*69.88*	4.81	25.31	*30.12*
Allergen avoidance	21.21	11.41	4.28	*36.90*	13.73	49.37	*63.10*

The results of the average PMT scale scores are shown in Table *3*. The perceived seriousness of hay fever and perceived *severity* accounted for 3.57 (SD = 0.726) and 3.62 (SD = 0.849), respectively. Both values were above the mean of the scale, nevertheless, did not indicate threat appraisal to be high. Regarding the response appraisal, the average allergy management measures score was 3.92 (SD = 0.711), indicating high perceived *response efficacy* of allergy management measures. The score for the *response costs* scale was 2.90 (SD = 0.829), indicating moderate expected effort associated with allergy management. Consequently, the benefits of hay fever management appeared to outweigh the required efforts. *Self-efficacy* had a score of 3.56 (SD = 0.550), indicating a moderate perceived ability to perform the target behavior.

Table 3: Averaged PMT scales

	Cronbach's α	**Mean (SD)**
Seriousness	0.713	3.57 (0.726)
Severity	0.867	3.62 (0.849)
Response efficacy	0.822	3.92 (0.711)
Response costs	0.796	2.90 (0.829)
Self-efficacy	0.665	3.56 (0.550)

The correlation coefficients of the average PMT scale scores are shown in Table 4. The perceived *seriousness* of the disease was strongly correlated with the perceived *severit*y of allergic symptoms (ρ = 0.48). The perceived *severity* was also moderately correlated with *response costs* (ρ = 0.30), indicating a higher perceived effort associated with higher symptom severity. The *response costs* showed a moderate negative relationship with *self-efficacy* (ρ = −0.34) and *response efficacy* (ρ = −0.32), suggesting that perceptions of one's own ability to perform the target behavior and perceptions of the efficacy of allergy management decrease with increasing symptom severity. *Response efficacy* was strongly correlated with *self-efficacy*, suggesting that both constructs reinforced each other.

Table 4: Correlation coefficients (Spemann's rho) between the PMT constructs

		(1)	(2)	(3)	(4)	(5)
Seriousness	(1)	-				
Severity	(2)	0.48**	-			
Response efficacy	(3)	0.10*†	0.02	-		
Response costs	(4)	0.18**	0.30**	-0.32**	-	
Self-efficacy	(5)	0.08	-0.06	0.48**	-0.34**	-

*Significance level $p < 0.05$, ** Significance level $p < 0.01$, † not significant due to multiple testing

4.2 Utilization of the various allergy management measures

Factors influencing the health related decisions regarding utilization of various allergy management measures are shown in Table 5. Three variables were found to exert a positive effect on the willingness to manage hay fever under medical supervision with self-efficacy, increasing the probability of medical supervision in almost 4 times (OR = 3.75, 95% CI: 2.36-5.97), and being the strongest predictor. Furthermore, the perceived seriousness of hay fever (OR = 2.41, 95% CI: 1.56-2.94) had a stronger effect in favor of medical help in comparison to the severity of the symptoms (OR = 1.57, 95% CI: 1.19-2.07).

Severity showed a significant positive effect on the decision in favor of hay fever management without medical support, increasing its probability by 60% (OR =1.60, 95% CI: 1.21-2.11). Females (OR = 1.75, 95% CI: 1.17-2.61) were significant likely to manage their hay fever self-responsible in comparison to men, although this finding was neglected by multiple testing. Those claiming to be treated by a doctor (OR = 0.44, CI: 0.28-0.69) were significant less likely to perform some additional self-responsible measures. This finding suggests allergic individuals rather to opt for one of the two alternatives, either self-responsible hay fever management or hay fever treatment under medical supervision. Although these groups still are not completely disjoint.

The construct severity (OR = 1.60, 95% CI: 1.13-2.26) and self-efficacy (OR = 2.41, 95% CI: 1.38-4.19) exerted a positive effect on the decision to take anti-allergic medication, with the latter being a substantial stronger predictor. The hay fever management under medical supervision and self-responsible hay fever management without medical supervision had an even stronger impact on the likelihood of the anti-allergic medication. Those receiving medical help were twice likely to take anti-allergic medication (OR = 2.18, 95% CI: 1.19-3.98), whereas allergic individuals dealing with their hay fever self-responsible were more than in 4.5 times likely to utilize the anti-allergic medication (OR = 4.61, 95% CI: 2.76-7.78). However, due to the multiple testing the effect of hay fever treatment under medical supervision was found to be not significant. Nevertheless, the results indicate a tendency which might be supported using a larger sample of the target population.

Only one variable has predetermined the decision to undergo the specific immunotherapy. Those study participants being treated by a doctor were 11 times likely to make use of this, the only curative therapy option (OR = 11.17, 95% CI: 6.81-18.30).

The symptom severity increased the likelihood of allergen avoidance (OR = 2.11, 95% CI: 1.59-2.79), whereas the raising perceived seriousness of the disease was associated with decreasing readiness to undertake avoidance strategies (OR = 0.71, 95% CI: 0.52-0.97). However, the latter was found to be not significant due to the multiple testing. The self-efficacy showed a positive effect on the use of allergen avoidance strategies (OR = 1.66, 95% CI: 1.06-2.55) but was neglected by multiple testing. Nevertheless, allergic individuals preferring self-responsible hay fever management without medical help were significantly less reluctant to make use of allergen avoidance strategies (OR = 2.43, 95% CI: 1.56-3.08).

Table 5: Association between the PMT constructs and allergy management measures

	Odds ratio (95% confidence interval)				
	Model 1 Medical supervision [a]	**Model 2** Self-responsible management[a]	**Model 3** Anti-allergic medication[a]	**Model 4** Specific immunotherapy [a]	**Model 5** Allergen avoidance[a]
Reference category (Yes [a])					
Seriousness	2.41 (1.56-2.94)**	0.99 (0.72-1.36)	0.98 (0.66-1.47)	1.09 (0.76-1.55)	0.71 (0.52-0.97)*†
Severity	1.57 (1.19-2.07)*	1.60 (1.21-2.11)*	1.60 (1.13-2.26)*	0.87 (0.64-1.18)	2.11 (1.59-2.79)**
Response efficacy	0.88 (0.64-1.23)	0.93 (0.67-1.29)	1.29 (0.86-1.92)	1.06 (0.73-1.52)	1.08 (0.78-1.49)
Response costs	1.09 (0.83-1.43)	0.85 (0.65-1.13)	1.10 (0.77-1.57)	1.24 (0.92-1.66)	1.27 (0.97-1.66)
Self-efficacy	3.75 (2.36-5.97)**	1.52 (0.97-2.37)	2.41 (1.38-4.19)**	1.45 (0.88-2.40)	1.66 (1.06-2.59)*†
Allergy experience	1.00 (0.98-1.02)	1.02 (1.00-1.05)	1.03 (1.00-1.07)*†	1.00 (0.98-1.03)	1.02 (1.00-1.04)
Gender (female)	1.11 (0.74-1.65)	1.75 (1.17-2.61)*†	1.41 (0.85-2.34)	0.70 (0.45-1.11)	1.21 (0.82-1.79)
Medical supervision [a]		0.44 (0.28-0.69)**	2.18 (1.19-3.98)*†	11.17 (6.81-18.30)**	1.42 (0.87-2.32)
Self-responsible management [a]			4.61 (2.76-7.78)**	1.11 (0.67- 1.86)	2.43 (1.56-3.08)**
Anti-allergic medication [a]				0.86 (0.45-1.62)	0.92 (0.55-1.54)
Specific immunotherapy [a]					0.89 (0.55-1.45)

*Significance level $p < 0.05$, ** Significance level $p < 0.01$, † not significant due to multiple testing, [a] Reference category "taking action"
Model 1: R^2= 0.19 (Cox & Snell), 0.25 (Nagelkerke), χ^2 (7) 114.79, $p < 0.00$; Model 2: R^2= 0.07 (Cox & Snell), 0.10 (Nagelkerke), χ^2 (8) 40.00, $p < 0.00$; Model 3: R^2= 0.19 (Cox & Snell), 0.30 (Nagelkerke), χ^2 (9) 119.011, $p < 0.00$; Model 4: R^2= 0.24 (Cox & Snell), 0.34 (Nagelkerke), χ^2 (10) 155.79, p < 0.00; Model 5: R^2= 0.14 (Cox & Snell), 0.19 (Nagelkerke), χ^2 (11) 83.89, $p < 0.00$

5. Discussion

The presented empirical investigation has revealed three major findings and makes the following key contributions. First, health-related decisions regarding the utilization of various hay fever management measures were substantially stronger motivated by threat appraisal than by response appraisal. Second, the perceived *severity* of symptoms was the dominant driver of threat appraisal, which facilitated health-related decisions. Third, *self-efficacy* was the only significant influencing factor of response appraisal affecting hay fever management decisions in allergic individuals.

In the consideration of these survey results, it must be noted that participation in this survey was voluntary, and the online questionnaire was also distributed to all students of the University of Augsburg. Thus, a large proportion of the study participants were young, well-educated allergic individuals. In this way, there is a certain degree of bias in the respondents' answers, as the study sample might represent a specific population. The possible bias was minimized through thoughtful and careful scale development based on interviews and a pretest with a sample from the target population. Furthermore, our analysis relied on participants' self-reported information concerning the utilization of different hay fever management measures and suffering from hay fever in general. The main limitation of the present survey was the relatively small sample size, which did not allow us to separately analyze the PMT influencing variables for each TTM stage.

Considering the assessed TTM stages, for each hay fever management measure, the largest share of participants was in either the pre-contemplation or maintenance stage. This finding indicates that most allergic individuals either had utilized an allergy management measure for a long time or did not even intend to it. Considering that the mean duration of allergies was almost 15 years, the included allergic individuals might have developed well-established habits concerning their approach to managing hay fever, especially if their existing behavior was perceived as reasonable and satisfactory. The only exception was found regarding the utilization of specific immunotherapy, for which the group of *nonactors* was larger than the group of *actors*. Furthermore, the largest portion of allergic individuals in the maintenance stage was found for the intake of anti-allergic medication, and the largest proportion of allergic individuals in the pre-contemplation stage was found for specific immunotherapy. The smallest share of allergic individuals was in the preparation stage across all questioned hay fever management measures except for specific immunotherapy. This finding suggests that individuals either quickly translate their intentions into action or fall back into the contemplation stage. A similar finding was reported by Schwarzer (1999), who emphasized that holding a strong intention does not guarantee the initiation of action. People may fail to address self-regulatory problems during behavior change due to various obstacles, such as changes in the surrounding context (Schwarzer 1999).

Three PMT constructs were shown to significantly influence health-related decisions concerning hay fever management. First, the perceived *seriousness* of hay fever had a significant positive effect on the decision to seek medical support and tended to be negatively related to allergen avoidance strategies. Second, perceived hay fever *severity* showed a significant positive effect on four allergy management measures, including treatment under medical supervision, allergy self-management, intake of anti-allergic medication, and allergen avoidance. Third, *self-efficacy* was found to be a significant predictor for three health-related measures, namely, treatment under medical supervision, intake of anti-allergic medication, and allergen avoidance. Additionally, *self-efficacy* tended to be positively related to allergy self-management. Interestingly, perceived *self-efficacy* had a substantially stronger effect on the decision to treat allergy under medical supervision than to practice allergy self-management. Remarkably, neither *response efficacy* nor *response costs* significantly influenced health-related decisions in hay fever management.

From the insights presented above, two conclusions can be drawn. First, since perceived symptom *severity* positively influenced all except one investigated allergy management measure, occurring allergic symptoms might be considered a trigger that induces action for allergy management. This conclusion is consistent with the results Meltzer et al. (2017), who showed hay fever sufferers to consider the onset of allergic symptoms to be a starting point for their medication (Meltzer et al. 2017). Second, anti-allergic measures are induced rather by threat appraisal than response appraisal. This observation is in line with the results of Ferrer and Klein (2015), who showed that health-related risk perceptions appear to play a more important role in motivating behavior change than perceived *response efficacy* (Ferrer and Klein 2015). Furthermore, this finding supports the so-called early-effectiveness hypothesis, which suggests the fear appeal to be more effective in prompting people to change behavior because they initially need to understand that a threat exists to develop motivation and increase their commitment to adopt new behavior (Nabi et al. 2008).

In addition to the influence of the PMT constructs, several allergy management measures were significantly related to each other. In particular, participants who engaged in allergy self-management were more likely to take anti-allergic medication, whereas allergic individuals being supported by a doctor in hay fever management were not. Two possible reasons might be responsible for these findings. First, the intake of medicine is the most obvious measure to address some health-related issues. Second, hay fever sufferers can buy several over-the-counter antihistamines without medical advice or prescription, which makes this allergy management option popular among hay fever sufferers (Tan et al. 2017; Lombardi et al. 2015). Italia et al. (2017) suggested that there might be a psychological threshold with regard to price of the over-the-counter medicine preventing allergic individuals from buying it (Italia et al. 2017). The popularity of this health related measure among the survey participants shows that this threshold is not exceeded. Medical supervision had no significant influence on the intake of anti-allergic medication, suggesting that medical doctors have further options to manage symptoms in allergic individuals, like specific immunotherapy. The use of specific immunotherapy, as the only curative treatment option, was significantly predicted only by medical supervision. On the one hand, this finding is self-explanatory because specific immunotherapy can be carried out exclusively under medical supervision. On the other hand, it remains unclear why none of the PMT constructs significantly influenced the decision to undergo specific immunotherapy. We suggest that allergic individuals seeking medical supervision completely rely on doctors' advice without considering further factors.

Positive, informed changes in health-related behavior are a desirable endpoint for the problem of inadequate allergy management. Educational interventions providing general knowledge about diseases and possible self-management strategies have been shown to have a beneficial effect on behavioral change and health outcomes in chronically ill individuals (Schaffer and Tian 2004; McCullough et al. 2016; Newman et al. 2004). Vulnerable individuals suffering from chronic health conditions are interested in receiving information on protective behavior related to their disease, especially regarding immediate-term advice on health management (Kreslake et al. 2016).

Concrete advice on health behavior during the pollen season might be beneficial for hay fever sufferers since even general health recommendations such as the importance of adequate sleep duration and appropriate body weight might be relevant to decrease the risk of suffering allergic symptoms (Nova et al. 2014). Based on the insights of the present study, health education for allergic individuals should be focused on variables related to threat appraisal, especially on the perceived *seriousness* of the disease. The manipulation of threat appraisal variables was shown to significantly change perceptions of disease and, consequently, the health behavior of people concerned (Milne 2000). However, it has to be taken into account that fear appeals have the potential to promote maladaptive responses, such as defensive psychological tactics to resist negative messages (Witte and Allen 2000). Particularly, if the threat appraisal is high and the possible response to threat is perceived to be ineffective. Fear appeals accompanied by increasing *self-efficacy* and *response efficacy* and decreasing *response costs* appear to be more effective (Sheeran et al. 2014). Information on coping that is aimed at increasing perceived *response efficacy* perceived *self-efficacy* is more effective in enhancing protective intention than health information that only increases the perceived threat (Ruiter et al. 2014). Since all motivators are rooted in the core belief that one has the power to achieve the desired change, the second focus of health education should be on increasing *self-efficacy* in allergic individuals. Indeed, promoting more positive attitudes can facilitate behavior change by increasing *self-efficacy* for healthier behavior (Sheeran et al. 2016). Interestingly, social support functions as mediator between perceived self-efficacy and adherence to health advice (Martos-Méndez 2015). Taking into consideration the rapid development of information technologies and increased use of the internet in medical questions by patients (Lausen et al. 2008), new technologies, connecting individuals with similar health concerns or providing relevant health-related information may offer further possibilities for promotion of healthy behavior among hay fever sufferers.

6. Conclusion

According to the insights offered by this study, a large share of allergic individuals do not engage in allergy management under medical supervision and tend to treat themselves self-reliantly. Since a large share of allergic individuals uses over-the-counter medication, obtaining first-line advice from a pharmacist might be considered a valuable alternative to medical supervision if the latter is not available for any reason. A promising possibility to facilitate health behavior among hay fever sufferers is the implementation of educational interventions aimed at helping individuals evaluate their existing hay fever management routines and obtain additional information on allergy management. Educational interventions to improve allergy management should focus on increasing awareness of health-related risks associated with allergic diseases for individuals with unappropriated allergy management. If such interventions are accompanied by the provision of information on various instrumental and psychological coping strategies to increase the perceived self-efficacy of allergic individuals, an even stronger effect on the desired target behavior might be achieved.

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5.3 Contribution 3: Acceptance of pollen applications in allergy management: An empirical investigation of influencing factors

Muzalyova A (2020)

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Abstract

Pollen allergy is one of the most prevalent chronic disease of respiratory track accounting for millions of sufferers worldwide, and causing substantial impairment of health related quality of life in people concerned. Despite essential advantages offered by pollen applications in allergy management, they are not widely used by the target population. It is still little known about resistance towards mobile health technologies in allergy management. This study aim to close this void by combining both, the IT and the health behavior perspective. Based on the Technology Acceptance Model (TAM) and the Protection Motivation Theory (PMT) the present study uncovers the key drivers of the pollen application acceptance. Empirical data collected among allergic subjects in Germany show the TAM influencing variables to have a substantially stronger positive effect on behavioral intention to accept a pollen application. Perceived *ease of use,* and perceived *usefulness* of a pollen application positively affect the *attitude* toward its use, which in turn enhances *behavioral intention* to adopt this mobile health solution. Among examined PMT influencing variables only perceived *seriousness* of allergy disease significantly affected the *behavioral intention*. The theoretical and practical implications of the key findings are discussed in context of application development addressing the target population of pollen allergy sufferers.

Keywords: Pollen applications, Pollen allergy management, Technology Acceptance Model, Protection Motivation Theory, mHealth

1. Introduction

The presence of information technology in today's life has expanded dramatically. More and more people are able to access the internet freely anytime and anywhere as they need it. As new technologies penetrate many dimensions of our every day's life, they offer new opportunities for gaining and exchanging information, as well as changing the landscape of the modern service sectors. These trends clearly open new opportunities in providing health care services to the patients. Traditionally, physicians play the central role in providing health services, health care information or advice to a patient. Increased availability of information on health-related topics and specific diseases, coming along ubiquity of internet access, change the traditional way of things. Increasingly, many people use the internet as a source of health care information prior to seeking care from a medical professional because of its immediate availability (Hesse et al. 2005). Particularly, around 36.8% of Germans consider the internet an important medium for health purposes, and almost 32% have a user account on an available health-related online platform (Lausen et al. 2008). Also social media is increasingly gaining importance as a medium for getting health advice (Crilly et al. 2019). The internet has also become a common resource for subjects coping with their chronical health condition, especially in adolescents (Jacobs and Popick 2012).

With the rapid development of multi-purpose mobile computing devices like smartphones, access to information in World Wide Web has become very fast and convenient, resulting in mobile phone application development boom. Health-related mobile apps appear to have certain features that lead to even better engagement success with patients in comparison to static health portals or internet in general or (Baldwin et al. 2017), as they allow to access health care services anytime and anywhere, overcoming geographical and temporal barriers. Mobile health (mHealth) is a promising new area in healthcare offering new cost-effective opportunities in promotion of preventive behavior and health monitoring, improving service delivery, empowering patients and enhancing patient-centered care (Andreoni et al. 2019). mHealth is defined as a medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital devices, and other wireless devices (WHO 2011). In the year 2010 about 70% worldwide citizens were interested in accessing at least one mHealth application and more than 200 million mHealth applications were downloaded with this trend continuing to grow (Silva et al. 2015). In the last decade a rapid growth of popularity of mobile disease management application for chronic health conditions was recorded (Patrick et al. 2008) with the vast majority of which are designed for patients managing their disease (Kao and Liebovitz 2017). This demonstrates that mobile health services might represent a promising technology, as they address the challenge of the rising number of chronic diseases related to lifestyle or dependent from environmental conditions, like pollen allergy. However, it remains a global challenge to provide mobile health information for all who need it (Hagar and Kartzinel 2016).

Pollen allergy, especially allergic rhinitis, also known as hay fever, remains a substantial health-related problem due to its high prevalence in children and adults all over the world (Pawankar 2014; Bauchau and Durham 2004; Passali et al. 2018). The symptoms of pollen allergy occur seasonally, and, dependent on perceived severity, can significantly impair different dimensions of the everyday life of pollen allergy sufferers (Meltzer et al. 2009; Blaiss et al. 2018; Devillier et al. 2016a). The severity of the occurring symptoms is significantly dependent on the health state of a subject but also on the current concentration of airborne pollen (Bastl et al. 2013). Chronic disease, like pollen allergy, requires long-term therapy in order to relieve the severity of occurring symptoms. Most anti-allergic measures, such as taking daily medicine or integration of supportive behavior into daily routines do not need constant medical supervision. Consequently, the management of seasonal pollen allergy is performed outside health care institutions by pollen allergy sufferers themselves, and requires a high degree of self-administration. An mHealth solution providing information on current pollen load as well as pollen forecasting for several days ahead can support pollen allergy suffers enabling them to take active measures in order to prevent severe allergic reaction. As already outlined by Kmenta et al. (2014) a pollen application can become an important aid in avoiding exposure to allergenic pollen, and planning medication and outdoor activities (Kmenta et al. 2014). The need for an innovative solution supporting allergic subjects in the allergy management is not to overlook: Allergic subjects reach for web-search engines like Google when looking for additional information on different allergy management options (Lombardi et al. 2009). Willson et al. (2015) have demonstrated a strong temporal relationship between regional pollen counts and internet searches for “allergy”, “allergies” and “pollen” (Willson et al. 2015). Finally, Kmenta et al. (2016) have detected a strong association between pollen information consumption and actual pollen concentration of allergenic species (Kmenta et al. 2016). Individuals using an environmental monitoring app providing among others information on current pollen load, stated the information on airborne pollen concentration to be extremely useful and helpful for raising awareness on the impact of environmental influences on health and well-being (Johnston 2018). Furthermore, pollen allergy sufferers using mobile health apps reported to be able to better control their health-related well-being due to the use of the mHealth application (Krebs and Duncan 2015). However, for allergy patients, to make use of this mHealth solution, they first need to perceive a pollen application as a useful tool for pollen allergy management. Despite possible advantages offered by regular use of pollen applications, only 30% of allergy sufferers in Germany make use of this kind of mHealth service (Muzalyova et al. 2019). The reasons for this resistance towards mHealth technologies in allergy management remain largely unresearched. The present study aims to close this void by investigating the key drivers of acceptance of mHealth technology in pollen allergy management combining the perspective of information system as well as health related behavior. The scholars focus mainly on the advantages of pollen applications for collecting relevant scientific information (Bousquet et al. 2017; Bousquet et al. 2018; Matricardi et al. 2020) without considering the motivating factors that foster sustained application use (Birkhoff and Smeltzer 2017). The objective of the present study is to focus on the perspective of potential end-user, and to examine cognitions, affects and preexisting conditions influencing adaption behavior of pollen applications in allergy management.

2. Conceptual Background

2.1. Technology Acceptance Model (TAM)

For new technologies to improve individuals' everyday life and health, they first have to be accepted by the potential users. Information technology research has introduced many competing models explaining adoption behavior of the users through different sets of acceptance determinants. Technology Acceptance Model (TAM) (Davis 1985) is one of the most influential theories focusing on this research topic. The TAM states that a user's intention to use a new technology is determined by two factors: Perceived usefulness and perceived ease of use. Perceived ease of use is defined as the extent to which a person believes that using a certain technology will be free of effort. Perceived usefulness describes degree to which a person believes that a new technology will improve his or her job performance (Davis et al. 1989). These two components positively affect the attitude toward a new technology, referring to an individual's positive or negative feeling about using this technology. Behavioral intention, being an individual's intention to actually use this technology is predetermined by perceived usefulness and attitude (Davis et al. 1989). Originally, TAM was developed to describe the adoption behavior of new technologies in organizational context (Davis 1985), but thanks to its simplicity and good explanation ability TAM is widely used in many other IT contexts including adoption of mHealth technologies (Zhao et al. 2018).

There is a significant body of research documenting the influence of the TAM's core variables on attitude and behavioral intention to adopt mHealth solutions of different kinds. Several studies (Deng et al.; Deng 2013; Zhao et al. 2018) have demonstrated a significant relationship between perceived usefulness and attitude toward using mobile health services. Cho (2016) investigating the continued use of health apps has outlined the influence of the perceived usefulness on behavioral intention to use mobile health services (Cho 2016). Sun et al. (2013) came to a similar conclusion when testing the utility of different technology acceptance models on utilization of mobile health services (Cho 2016;

Sun et al. 2013). An extensive meta-analysis of the TAM has acknowledged significant influence of the perceived ease of use, and perceived usefulness attitude toward a new technology resulting in behavioral intention to use this technology in a broad IT context (Schepers and Wetzels 2007), as well as, in the area of mHealth adoption (Zhao et al. 2018). Finally, perceived ease of use was shown to be significantly associated with perceived usefulness of mobile health services (Guo et al. 2012; Hung and Jen 2012). Based on these findings, it is hypothesized:

H1: Perceived usefulness of a pollen application positively affects attitude toward its use

H2: Perceived usefulness of a pollen application positively affects behavioral intention towards its use

H3: Perceived ease of use of a pollen application positively affects its perceived usefulness

H4: Perceived ease of use of a pollen application positively affects attitude toward its use

H5: Attitude toward a pollen application facilitates behavioral intention toward its use

The simplicity of TAM is a great advantage of the model, undoubtedly contributing to its wide use in IT technology acceptance. At the same time it is its disadvantage since this model disregards further potential influencing factors (Sun et al. 2013). Several studies have extended traditional TAM constructs with further potential influencing variables yielding significantly better results in explaining acceptance behavior (Moon and Kim 2001; Mackert et al. 2016; Cho 2016).

2.2. Protection Motivation Theory (PMT)

In order to address all possible influencing factors determining the adoption of an mHealth technology, it is important to take the health context of the technology's use into consideration. Referring to Nutbeam (1998) health behavior is any activity undertaken by a person, regardless of actual or perceived health status, for the purpose of promoting or maintaining the health state, whether or not such behavior is objectively effective towards that end (Nutbeam 1998). Since the use of a pollen application is an activity directed toward protection and maintenance of the user's health-related well-being, the acceptance of mobile health technologies might be regarded as a health behavior. Thereby, an additional consideration of the health behavioral models is indispensable and might provide a strengthened theoretical base when explaining the acceptance of pollen applications. One of the most prominent health behavior models is the Protection Motivation Theory (PMT) introduced by Rogers (Rogers 1975). The model states that two appraisal processes are responsible for health-relevant decisions of an individual. Threat appraisal consists of perceived vulnerability, describing to which extent a person believes to be prone to a certain disease, and perceived severity, defining the suspected symptom severity or potential harm to one's health caused by this disease. Coping appraisal consist of three constructs: Response efficacy, response costs and self-efficacy. Response efficacy is defined as expected advantage in preventing the disease or reduction of its harmful impact on health through a target behavior. Response costs are the expected effort needed to perform a certain health related behavior, and self-efficacy refers to one's belief of being capable to perform the target behavior consequently and regularly (Lippke and Renneberg 2010).

Considering the definition of the PMT constructs, both core TAM variables, namely perceived usefulness and perceived ease of use, are closely related to the response appraisal of the PMT. Since perceived usefulness in the TAM describes advantages of the use of a new technology in achieving certain goals, it can be considered a special case of response efficacy in the PMT, or vice versa. Perceived ease of use in the TAM is related to the response costs in the PMT, as it defines efforts arising from adoption of a new technology whereas the response costs reflect the effort needed to perform the target behavior. With regard to these content-related similarities of the theoretical constructs of the TAM and the PMT, it is meaningful to consider only three remaining PMT's variables (perceived vulnerability, perceived severity and self-efficacy) as the utility and effort arising from the use of a pollen application is already inquired by the TAM influencing variables. Furthermore, since pollen allergy sufferers do have an allergic disorder, they do not have to appraise their vulnerability to this disease. Due to common trivialization of pollen allergy by society and allergy sufferers themselves, several studies suggest the concept of perceived seriousness of allergy to be a significant influencing variable of health related behavior (Muzalyova et al. 2019). Particularly, perceived seriousness of allergy was shown to be positive related to readiness to be supervised by medical personnel in allergy management (Muzyalova and Brunner 2020). Thereby, it appears reasonable to exchange the concept of perceived vulnerability with perceived seriousness of the allergy disease in the conceptual model.

Although, the PMT has been widely used to explain the adoption of the traditional healthcare services by patients (Milne 2000; Floyd et al. 2000), its application in the mHealth context is rarely found (Sun et al. 2013). Gao et al. 2015 have illustrated some of the PMT constructs, such as, perceived severity and self-efficacy to affect the behavioral intention for adaption of wearable technologies in healthcare (Gao et al. 2015). Furthermore, Lv et al. 2012 have revealed self-efficacy to have a significant impact on adaption intention of mHealth solutions (Lv et al. 2012). To a similar conclusion came Fox and Connolly (2018) when examining mHealth adoption across generations (Fox and Connolly 2018). According to Sun et al. 2013 vulnerability and self-efficacy could be proven to exert a significant influence on adoption intention of health-related technologies (Sun et al. 2013). Due to presented state of research, it is hypothesized:

H6: Perceived severity of allergic symptoms positively affects behavioral intention toward the use of a pollen application

H7: Perceived seriousness of allergy positively affects behavioral intention toward the use of a pollen application

H8: Perceived self-efficacy positively affects behavioral intention toward the use of a pollen application

2.3. Behavioral intention and actual utilization of pollen applications

Several pollen applications are already available on the German market of mHealth solutions and can be used by the target population. Nevertheless, mHealth remains a relatively young branch in disease management. Thus, it is expected for the wide audience of pollen allergy sufferers not to be aware of this allergy management option. Consequently, in some cases non-use of pollen applications is caused singly by non-awareness of the existence of pollen applications. By participating in the present study, pollen allergy sufferers not familiar with pollen applications might be sensitized to its use and develop an intention of its utilization. Due to this consideration, it appears reasonable to inquire not only the actual utilization of the pollen applications by pollen allergy sufferers, but also their willingness to adopt such a mHealth solution. As the Transtheoretical Model (TTM) defines the adoption of a health behavior as a process passing through several stages starting with unawareness of a problem or its handling strategies (Precontemplation) to the target behavior performed regularly (Maintenance) (Prochaska and Velicer 1997), it is meaningful to inquire the actual utilization of pollen applications using five stages of change defined by the TTM. The actual behavior reflecting the acceptance, and utilization of a pollen application is expected to be positively predetermined by the behavioral intention. Consequently, it is hypothesized:

H9: Behavioral intention positively affects the actual utilization of the pollen applications

The conceptual model in its entirety can be observed in Fugure 1 representing the theoretical model and hypotheses.

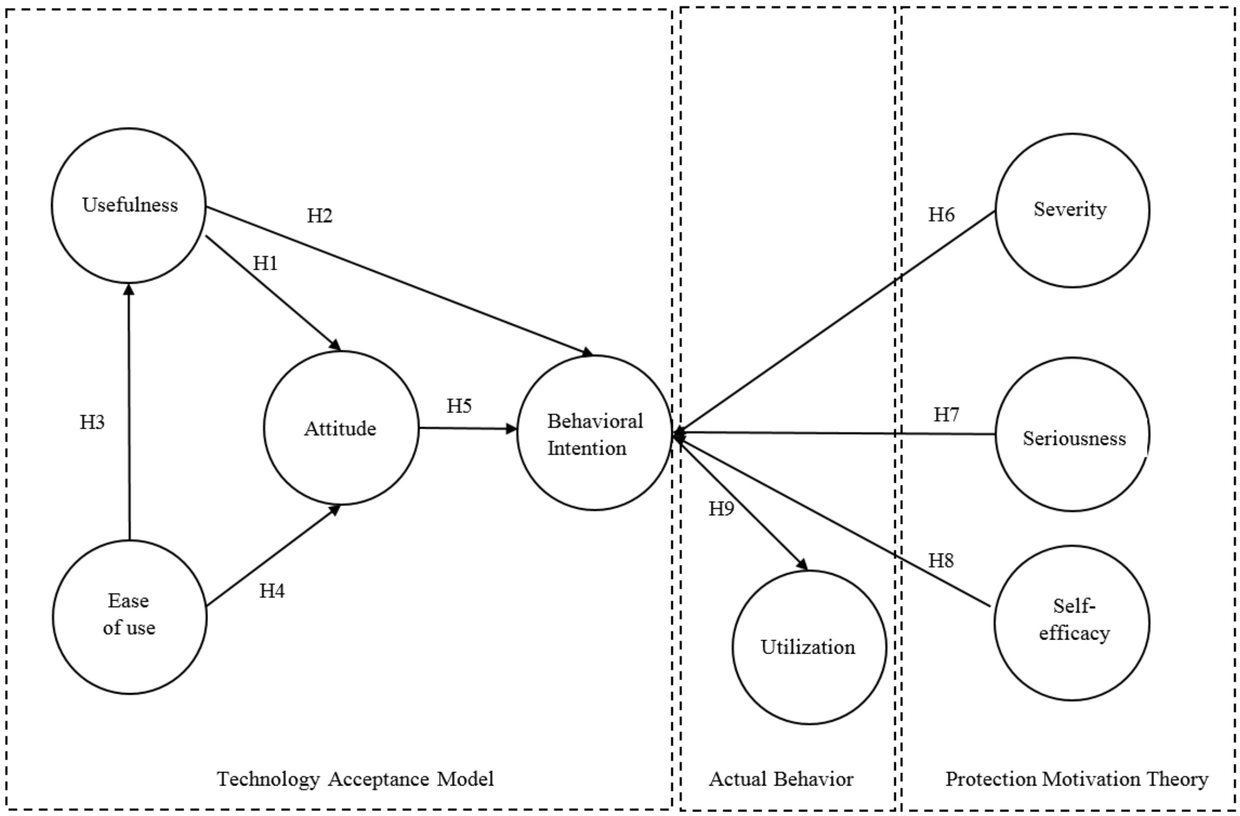

Figure 1: Theoretical model of adoption of mobile-based pollen application in allergy management

3. Materials and methods

3.1 Participant recruitment and data collection

The research questions proposed by this study were answered following a cross-sectional online experiment that was conducted in early spring 2020 with a sample from Germany. For increased realism, participants were recruited from the individuals being participants in social media groups addressing allergy sufferers. The study participants were required to be pollen allergy sufferers sensitized exclusively against pollen of at least one allergenic species and not be allergic against perennial allergens like animal dander or dust mites. To limit the present study to pollen allergy sufferers exclusively, several questions about allergy characteristics, such as allergenic agent or years suffering from allergy, were included in the questionnaire. Participants leaving these questions out were not considered as eligible.

The respondents' comprehension of the developed scales was tested using a sample of 15 individuals from the target population. The pre-test participants were asked to fill in the questionnaire and to point out the difficulties to understand items, and items that were inapplicable to them in general. Due to results of the pre-test only minor changes in wording of some items were necessary.

3.1. Study design

The study consisted of two stages: In the first stage a fictional pollen application was presented to the participants. In the second stage the respondents were asked to access the presented scenario. The use of such a scenario is a well-established approach in information system research (Hertzum 2003). Due to its cost-effectiveness and low risks for sensitive research fields like healthcare, it is suitable for different research areas including acceptance of the mHealth solutions, especially if the majority of the study population is expected not to be aware of such mHealth technologies.

In the first stage, all informed about the purpose of the study and consenting participants received an instruction describing a mobile based pollen application. The hypothetical pollen application focused on providing information about the current pollen load to pollen allergy sufferers as well as informing them about expected pollen loads for the several coming days. Moreover, the scenario envisages the possibility of entering one's occurring allergic symptom in a pollen diary. The presented pollen application also offered a customization option by choosing allergenic species to be shown on the main screen, or setting a pollen alarm at a specific time of the day. Since the developer of this pollen application is not a healthcare specialist, the scenario was not urging participants to take any concrete allergy management measures, such as taking anti-allergic medication or undergoing specific immunotherapy. The intended pollen application focused mainly on providing pollen information as a basis for supporting pollen allergy sufferers in allergy management. For increased realism, study participants were also presented several mobile phone screenshots, showing planned design and intendent functionality of the pollen application. According to the scenario the presented pollen application was to be provided free of charge for an undefined period of time.

In the second stage, following the pollen application scenario, an online survey inquired participants' assessment of the presented fictitious pollen service (perceived ease of use, perceived usefulness and attitude toward its use), several allergy characteristics and preexisting beliefs (perceived seriousness of disease allergy, perceived severity of the symptoms and perceived self-efficacy), as well as relevant demographical variables. All items related to the TAM latent constructs were captured with five-step Likert-type scales adapted from reliable scales validated in previous research (Sun et al. 2013; Cocosila 2013; Deng 2013; Featherman and Pavlou 2003; Guo et al. 2012; Moon and Kim 2001) adjusted to specifics of pollen allergy and mHealth solution focusing on its management. The items related to the PMT latent construct were adopted from the previous study conducted by Muzalyova and Brunner (2020) investigating the health-related behavior of pollen allergy sufferers, measured with five-step Likert-type scales (Muzyalova and Brunner 2020). Actual utilization of pollen applications was inquired by one item consisting of five statements referring to the five TTM stages of change with respect to acceptance of pollen applications.

A total of N = 319 allergic subjects filled in the online questionnaire. Twelve of them were excluded since they did not fulfill the inclusion criteria due to additional sensitizations against animal dander (n = 2) or dust mites (n = 5), or having missing information about their allergy (n = 5). Consequently, N = 307 questionnaires were found to be eligible for the data analysis.

3.2. Data analysis

The demographic variables collected in the course of the study are presented as frequencies or mean values with respect to its scale of measurement. The theorized conceptual model describing acceptance of pollen applications was analyzed with covariance-based structural equation modeling (CB-SEM) technique using IBM SPSS AMOS 25. The CB-SEM was chosen because of its suitability to the research goal of the present study referring to theory testing (Hair et al. 2014), and due to current criticism of the partial least squares SEM (Rönkkö et al. 2016). A two-step approach as introduced by Anderson and Gerbing (1988) was applied in the present study to analyze the data collected (Anderson and Gerbing 1988). Specifically, the validation of the measurement model was followed by the evaluation of the structural model.

Structural equation modeling was estimated using maximum likelihood estimates. The overall fit of the proposed model was evaluated using a number of goodness-of-fit indices referring to absolute, comparative, and residual aspects of model fit. In this study χ^2/df ratio, Tucker-Lewis index (TLI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSE) are reported. The χ^2/df ratio less than 2.0, TLI and CFI greater than 0.9 are considered to indicate acceptable model fit (Byrne 2013). The RMSE has been recognized by scholars as one of the most informative goodness-of-fit criteria in CB structural modelling, since it takes into account the error of approximation in the underlying population and it estimates how well the model would fit if all parameter values would be chosen optimally. An RMSE-value of <0.10 indicate an acceptable model fit and a value <0.05 refers to a good model fit (Byrne 2013).

The data recording the latent variables contains no missing values due to the data collection method. Therefore, after the assessment of the presented conceptual model, modification indexes were examined in order to uncover possible improvements of the theorized model. Possible modification will be discussed from the statistical as well as conceptual point of view.

4. Results

4.1 Descriptive statistics

Analysis indicated that females constituted 62.9% (n = 193) of the total study population. The three most common sensitizations against allergenic pollen were grass, birch and hazel, with 48.5% (n = 149), 28.0% (n = 86), and 14.7% (n = 45) respectively. On average the study participants were suffering from the pollen allergy for 14.98 (SD = 8.743) consecutive years. As expected, a relatively small share of the collective questioned reported to use pollen applications in allergy management 27.0% (n = 83), with 5.5% (n = 17) using this mHealth solution frequently, and 21.5% (n = 66) using a pollen application rather seldom. Non-users accounted for 72.9% (n = 224) and can be divided in three groups according to their readiness to adopt a pollen application. The share of 8.1% (n = 25) was intended to start using a pollen application in allergy management, 51.1% (n = 157) was contemplating the adaption of a pollen application, and 13.7% (n = 42) were totally reluctant toward the utilization of pollen applications.

4.2 Measurement model

During the first stage, the reliability and validity of the constructs were assessed to guarantee the appropriateness of the measurement model. For the inquired latent variables reliability, composite reliability (CR), and average variance extracted (AVE) were examined. The final result of the factor analysis is outlined in Table. Analysis showed the CR and AVE to be above the recommended values of 0.5 and 0.7, respectively (Gefen et al. 2011). Factor loadings were generally high above 0.7 for almost all items with only a few exceptions. The Cronbach's alpha was above the recommended value of 0.7 for all latent constructs but for the Ease-of-Use-scale. Due to appropriate factor loading of all indicators of the mentioned construct, and acceptable CR and AVE, the scale was considered eligible and included in further analysis without changes. Overall, the presented results allow the conclusion that all captured latent constructs have the appropriate reliability and convergent validity.

Table 1: Statistics of the measurement model

Item	Mean	Standard deviation	Factor loading	CR (Cronbach's alpha; AVE)
EOU1	4.00	0.802	0.779	
EOU2	3.85	0.859	0.762	
EOU3	3.81	0.776	0.758	
	3.89	0.635		0.810(0.681; 0.587)
USF1	3.74	0.903	0.724	
USF2	3.70	0.937	0.795	
USF3	3.89	0.902	0.763	
	3.77	0.758		0.805(0.773; 0.579)
ATT1	3.81	0.958	0.958	
ATT2	3.63	0.694	0.894	
ATT3	3.71	0.670	0.898	
	3.72	0.791		0.784(0.828; 0.550)
BI1	3.82	0.984	0.830	
BI2	4.08	0.828	0.802	
	3.95	0.839		0.800(0.824; 0.666)
SER1	3.37	1.158	0.794	
SER2	3.54	1.152	0.861	
SER3	3.07	1.222	0.713	
	3.32	1.010		0.834(0.812; 0.627)
SEV1	4.03	0.936	0.883	
SEV2	3.62	1.150	0.832	
SEV3	3.81	1.054	0.858	
	3.77	0.931		0.893(0.878; 0.736)
SE1	3.48	0.879	0.810	
SE2	3.24	0.956	0.782	
SE3	3.63	0.896	0.799	
	3.45	0.742		0.839(0.748; 0.635)

EOU: Ease of Use, USF: Usefulness, ATT: Attitude, BI: Behavioral Intention, SER: Seriousness, SEV: Severity, SE: Self-Efficacy

Table 2: Loadings and cross-loadings of the latent constructs

Item	EOU	USF	ATT	BI	SER	SEV	SE
EOU1	0.779	0.229	-0.027	-0.031	-0.012	0.008	0.207
EOU2	0.762	-0.084	0.040	0.036	0.120	-0.143	-0.028
EOU3	0.758	0.057	0.132	0.142	-0.135	0.062	0.062
USF1	0.062	0.724	0.247	0.241	0.042	-0.136	0.214
USF2	0.019	0.795	0.160	0.150	-0.015	0.142	0.050
USF3	0.112	0.763	0.282	0.276	0.015	0.018	0.119
ATT1	0.072	0.188	0.958	0.742	0.036	0.034	0.079
ATT2	0.120	0.204	0.894	0.658	-0.117	-0.041	0.079
ATT3	0.091	0.356	0.898	0.660	-0.023	-0.087	0.095
BI1	0.049	0.118	0.632	0.830	0.179	0.069	0.024
BI2	0.068	0.092	0.557	0.802	0.151	0.179	0.068
SER1	-0.058	0.020	0.093	0.085	0.794	0.305	0.013
SER2	-0.008	0.025	0.025	0.011	0.861	0.108	-0.020
SER3	0.053	-0.031	0.113	0.101	0.713	0.442	-0.010
SEV1	0.016	0.009	0.046	0.052	0.205	0.883	-0.073
SEV2	-0.084	0.044	0.047	0.032	0.237	0.832	-0.041
SEV3	-0.021	-0.005	0.049	0.052	0.181	0.858	-0.087
SE1	0.114	0.014	0.012	0.013	0.161	-0.045	0.810
SE2	0.000	0.183	0.091	0.088	-0.058	-0.090	0.782
SE3	0.099	0.112	0.123	0.117	-0.117	-0.044	0.799

EOU: Ease of Use, USF: Usefulness, ATT: Attitude, BI: Behavioral Intention, SER: Seriousness, SEV: Severity, SE: Self-Efficacy

The discriminant validity was assessed by a visual examination of the matrix of loadings and cross-loadings of the latent constructs. As shown in Table 2, the items load more on the latent constructs they are supposed to load. Furthermore, the square roots of AVE values for all construct are larger than the correlations with other constructs (Table 3). Consequently, it can be concluded that the constructs show appropriate discriminant validity. Since the reliability and construct validity conditions were met, the CB-SEM analysis continued with the structural part.

Table 3: Correlations and square roots of average variance extracted

	EOU	USF	ATT	BI	SEV	SER	SE
EOU	**0.766**						
USF	0.357	**0.761**					
ATT	0.299	0.667	**0.742**				
BI	0.215	0.545	0.701	**0.816**			
SEV	-0.061	0.041	0.090	0.183	**0.792**		
SER	-0.001	0.013	0.027	0.297	0.638	**0.858**	
SE	0.409	0.348	0.289	0.176	-0.176	-0.043	**0.797**

EOU: Ease of Use, USF: Usefulness, ATT: Attitude, BI: Behavioral Intention, SER: Seriousness, SEV: Severity, SE: Self-Efficacy

4.3 Structural model

Structural model analysis was conducted by evaluating path coefficients and significance levels after running SPSS (Statistical Package for the Social Sciences, Version 25.0) Amos with a *Bollen-Stine* bootstrap with 200 re-samples. Results are outlined in Figure 2 and Table 4. The goodness-of-fit indices indicated that the hypothesized model represents the data quit well. In practical terms, the χ^2/df ratio accounted to 1.98 sitting below the recommended value of 2.0. The TLI and CFI accounted for 0.923 and 0.934 representing an appropriate model fit. The RMSE achieved the value of 0.057 also indicating a good mode fit. In total, five out of the nine defined hypotheses were supported. As expected, the perceived ease of use positively affected the perceived usefulness of a pollen application, which was significantly associated with the positive attitude toward the use of a pollen application in allergy management. Surprisingly, neither did the perceived ease of use affect the attitude toward pollen applications, nor was the perceived usefulness significantly associated with the behavioral intention. Nevertheless, the attitude had a strong positive effect on behavioral intention. Furthermore, the behavioral intention represented a significant motivator of the actual utilization of mobile-based pollen applications in allergy management. Considering the PMT influencing variables, only perceived seriousness of disease allergy revealed a significant positive influence on the behavioral intention to adopt a pollen application.

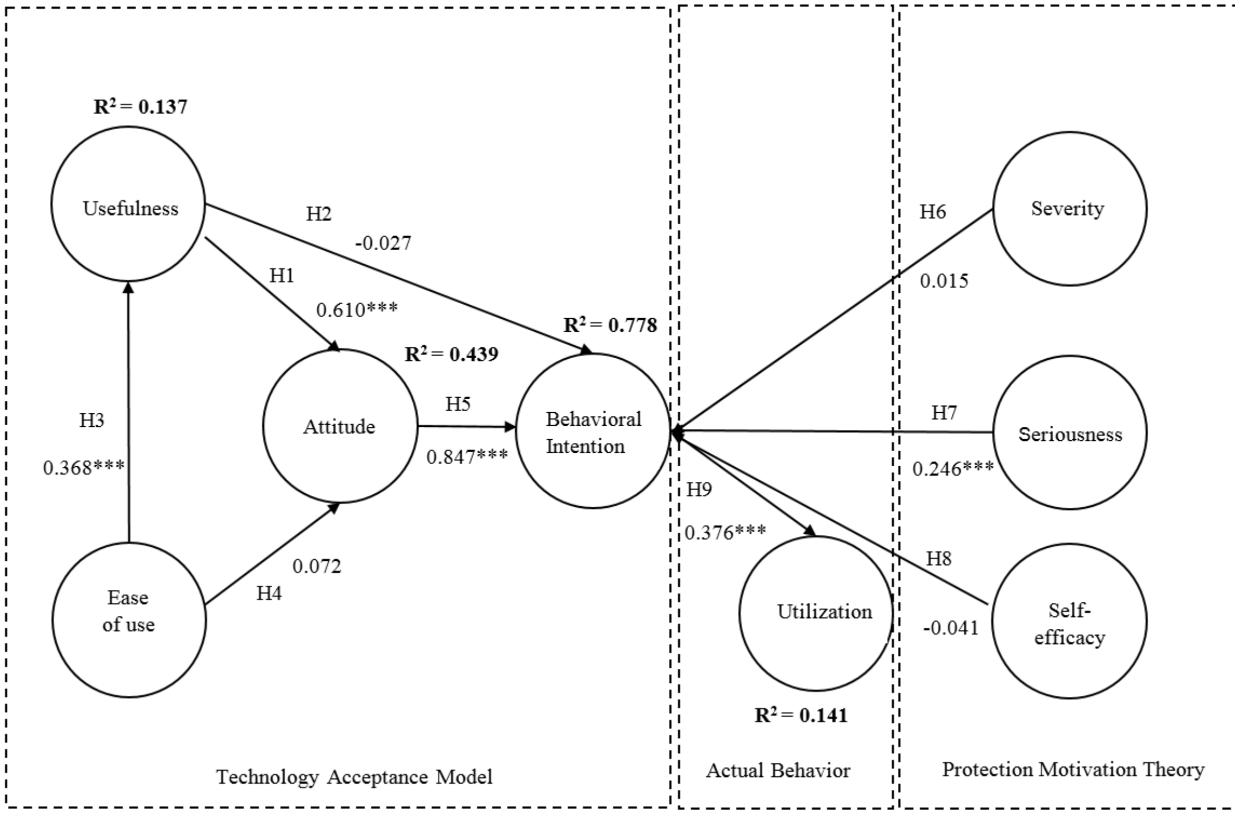

Figure 2: Structural evaluation of the model of pollen application adoption in allergy management (Model: Chi-square = 356.077, df = 180, CFI = 0.934, TLI = 0.923, RMSE = 0.057; Significance levels: *= 0.05, **=0.01, ***=0.001)

The proposed model showed relatively high explanatory power for two endogenous constructs: The variance explained for attitude toward use of pollen applications accounted for R^2 = 0.439 and for behavioral intention R^2 = 0.778. The perceived usefulness (R^2 = 0.137) and actual utilization of pollen applications (R^2 = 0.141) had a much lower coefficients of determination.

Table 4: Summary of the hypothesis test results

Hypothesis	Path coefficient	*p*-Value	Outcome
H1: USF->ATT	0.610	<0.001	Holds
H2: USF->BI	-0.027	0.702	Rejected
H3: EOU->USF	0.368	<0.001	Holds
H4: EOU->ATT	0.072	0.269	Rejected
H5: ATT->BI	0.647	<0.001	Holds
H6: SEV->BI	0.015	0.746	Rejected
H7: SER->BI	0.246	<0.001	Holds
H8: SE->BI	-0.041	0.413	Rejected
H9: BI->UTL	0.376	<0.001	Holds

EOU: Ease of Use, USF: Usefulness, ATT: Attitude, BI: Behavioral Intention, SER: Seriousness, SEV: Severity, SE: Self-Efficacy, UTL: Utilization

The examination of the modification indexes revealed a significant improvement of the model fit by adding a regression path from perceived self-efficacy to perceived ease of use and perceived usability indicating the potential decrease of discrepancy by 24.788, and 19.412 respectively. The proposed modifications were implemented stepwise in the conceptual model with respect to the expected discrepancy decrease. As can be seen in Table 5, the implemented modifications achieved a substantial improvement in overall fit of the model in all captured goodness-of-fit indexes, with CFI rising up to 0.950 and RMSE decreasing under 0.05 level.

Table 5: The goodness-of-fit summary of the tested models

Model	Chi-square	df	Chi-square/df	CFI	TLI	RMSE
1	356.077	180	1.98	0.934	0.923	0.057
2	329.871	179	1.84	0.944	0.934	0.052
3	312.051	178	1.75	0.950	0.941	0.049

Model 1: original conceptual model. Model 2: additional SE -> EOU path.
Model 3: additional SE -> USF path.

The modified structural model is presented in the Table 5. According to the results, self-efficacy positively affected both, the perceived ease of use and the perceived usefulness of a pollen application with the relationships being of comparable strength. Several changes of path coefficients arose due to the modification of conceptual model. The biggest change was observed in the path connecting the perceived ease of use and the perceived usefulness, decreasing from 0.368 to 0.246, as variation of the perceived usefulness was also explained by self-efficacy. The modification also resulted in increased explanatory power of the endogenous construct usefulness changing from $R^2 = 0.137$ to $R^2 = 0.220$, still remaining relatively low. The increase in the explanatory power of the constructs attitude ($R^2 = 0.451$) and behavioral intention ($R^2 = 0.788$) were observed but are in absolute terms rather negligible.

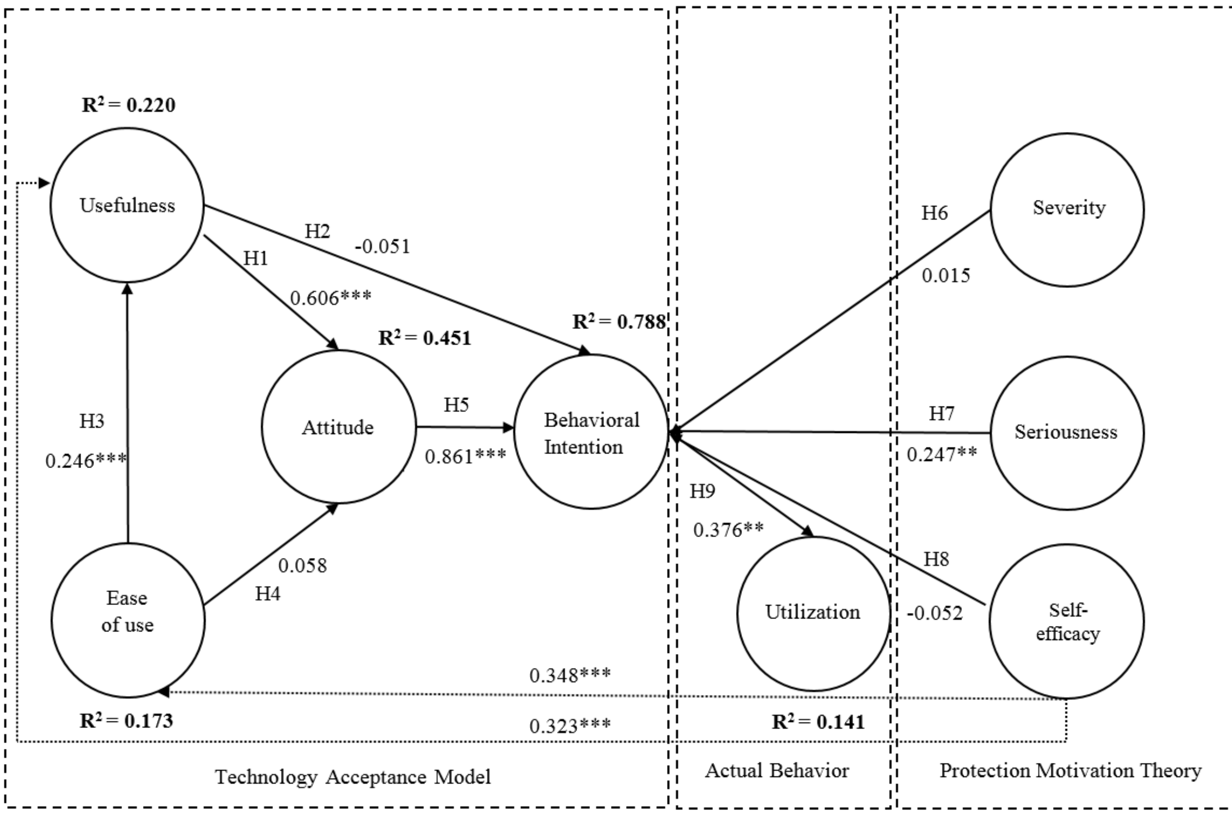

Figure 3: Structural evaluation of the modified model of pollen application adoption in allergy management

(Model: Chi-square = 312.051, df = 178, CFI = 0.950, TLI = 0.941, RMSE = 0.049; Significance levels: *= 0.05, **=0.01, ***=0.001)

5. Discussion and implications

5.1. Key findings and contributions

The main scope of this scientific study was to understand the role of several influencing variables on acceptance of mHealth technologies in allergy management. This research has three major findings, and makes following key contributions.

First, the collected empirical data shows only a small share of allergic subjects to be totally reluctant toward use of pollen applications in allergy management. Second, the examined conceptual model uncovered relevant factors facilitating the acceptance of pollen applications in allergy management.

Particularly, users' positive attitude enhanced by a cognitive response on implemented design features of a pollen application might be the main focus when developing a new pollen application. Third, the perceived seriousness of disease allergy is shown to enhance the behavioral intention of pollen application adoption. In combination with perceived usefulness, being a significant influencing variable on the attitude toward application use, it can be concluded that the purpose of this technology in instrumental support of allergy management is the main driver of its adaption.

Taking the above mentioned points into consideration, the present study not only uncovers pollen allergy suffers' interest in modern, IT-driven supporting tools in allergy management, but also delivers insights on the key drivers of their use.

5.2. Theoretical implications

The present study was conceptualized to explain the adaption behavior of pollen applications through pollen allergy sufferers combining the IT- and health behavior perspectives. Therefore two research questions each for the mentioned perspectives were defined. The first proposed research question was: *What is the effect of the TAM influencing variables, such as perceived usefulness, perceived ease of use, and attitude on intention and adoption behavior of a mobile based pollen application by allergic subjects?* According to the presented results, perceived ease of use positively and significantly influenced the perceived usefulness of a pollen application. The latter had a strong positive influence on the attitude toward the use of pollen applications which is in line with previous research (Deng 2013; Deng et al.; Hung and Jen 2012; Sun et al. 2013). As expected, positive attitude toward the pollen application had a strong positive affect on behavioral adoption intention (Deng 2013; Deng et al.; Hung and Jen 2012). Contrary to the hypothesized conceptual model, perceived ease of use had no significant influence on the attitude toward proposed mHealth solution for allergy management. However, this result can also be found in several empirical studies investigating mHealth acceptance along the TAM framework (Deng 2013; Deng et al.). The perceived usefulness had a substantially larger total effect on behavioral intention than perceived ease of use. The presented results allow the conclusion, that pollen allergy sufferers assess a pollen application primarily based on its potential to improve allergy management, rather than on effort needed for its adoption. Recent empirical evidence supports the existence of a stronger dependence on utility than on the lower complexity when adopting a new technology (Schepers and Wetzels 2007). Moreover, after the users gain enough experience with a new technology, perceived ease of use might lose its significant role in technology continuance and might be overshadowed by other factors (Bhattacherjee 2001). Taking into account the omnipresence of mobile based applications in our everyday life (Silva et al. 2015), the majority of the potential mHealth users might have substantial experience with various kinds of applications, also in health related context (Krebs and Duncan 2015), raising their confidence to handle any new mobile-based technology.

The second posed research question was: *What is the effect of the PMT influencing variables, such as, perceived severity, perceived seriousness of disease allergy, and expected self-efficacy on intention and adoption behavior of a mobile based pollen application by allergic subjects?* Only one examined PMT variable was found to significantly influence the behavioral intention. Perceived seriousness of disease allergy positively affected the adoption intention of a pollen application. The strength of the effect of perceived seriousness of allergy was comparable to the effect of the perceived ease of use on behavioral intention. Contrary to presented results, Gao et al. (2015) demonstrated in his study the perceived severity, vulnerability and self-efficacy to significantly affect customers' acceptance of health related wearable technologies (Gao et al. 2015). Surprisingly, the present study has not obtained evidence of a significant relationship between perceived self-efficacy and behavioral intention, although, this dependency was shown in several empirical studies examining acceptance of mHealth solution across various potential target groups (Lv et al. 2012; Sun et al. 2013). However, in the explorative phase of the model testing, a significant effect of self-efficacy on the perceived ease of use as well as on the perceived usability was indeed demonstrated. The concept of self-efficacy adopted from the PMT reflects one's belief to be capable to perform the target behavior consequently and regularly (Lippke and Renneberg 2010). According to the give definition, self-efficacy requires a high degree of self-administration and self-discipline in any kind of target behavior. These personal traits might be of a great advantage when adopting a new technology due to better ability to overcome difficulties and resist frustration arising from the effort required. Referring to Bandura (2004) the main sources of high self-efficiency expectations is performance accomplishment, or mastery experience, and vicarious experience (Bandura 2004). This implies the possibility to transfer experience made in a similar context to a new situation, for individuals having a high self-efficacy expectation. Thereby, individuals having a generally good experience using mobile application might expect themselves to easily manage a pollen application even if not familiar with its use. Furthermore, individuals attributing themselves as self-efficacious assume to succeed in intendent actions if required effort is applied (Bandura 1998). This allows an assumption that self-efficacious pollen allergy sufferers expect themselves to achieve perceived benefit from a pollen application, if its use is intended. From this point of view, the influence of self-efficacy on perceived ease of use and perceived usability appear reasonable. However, the relationship between self-efficacy and the perceived ease of use and the perceived usefulness found in the present study, has to be cross-validated in a different sample to assure its validity. Furthermore, in given research paradigm, it appears reasonable to control for general mobile application experience and

IT literacy, since it might be significantly associated with the perceived use and the perceived usefulness across various kinds of mHealth applications (Mackert et al. 2016).

5.3. Practical implications

According to the general definition of the TAM, design features of a mHealth application predetermine a cognitive response reflecting user's perceived usefulness and the perceived ease of use, resulting in an affective response, representing an attitude toward use of a new technology. In turn, the attitude induces a behavioral response in terms of behavioral intention and actual use of a new system (Davis 1985). Since the TAM influencing variables, representing the cognitive response to introduced scenario have a significantly greater influence on behavioral intention in comparison to the PMT influencing variables, it can be concluded that the way a pollen application is conceptualized and designed is more important than allergy characteristics or preexisting beliefs. This conclusion has two main implications for the goal of increasing the acceptance of pollen applications among pollen allergy sufferers. Firstly, the developers of mobile health applications, particularly of pollen applications, have to set a special focus on implementing features perceived as beneficial and explicitly desirable by the end-user. Secondly, mobile-based pollen applications should possibly address all categories of potential user's regardless of their disease characteristics, as those will not influence the ultimate adoption decision. Consequently, to get more traction, pollen applications have to better address the needs of target population but also gain more visibility by pollen allergy sufferers. The most influential IT-driven factor enhancing positive attitude toward a pollen application and, thus, behavioral intention, is perceived usefulness. Among allergy related factors, perceived seriousness of disease significantly influences behavioral intention of its acceptance. As allergic subjects taking their disease seriously tend to properly manage their allergy (Muzyalova and Jens O. Brunner 2020), it can be assumed that the usefulness of a pollen application will be assessed in first line based on the health content provided by this mHealth solution. The scenario presented in the first stage of the online experiment focused specifically on a pollen application as a tool providing information about current pollen load, as well as, pollen information several days ahead in order to support allergy management. That implies that providing high quality pollen information without any gaps during the whole pollen season, and its presentation ensuring the comprehensibility by the broad audience of the target population, represent essential features of a pollen application to ensure its sustained use. Following this track, pollen application developers might face several challenges. Currently, the development of smartphone-based health applications is mainly disconnected from the control and monitoring of provided contents in terms of scientific validity and understandability by users (Bert et al. 2014). Despite rapid proliferation of mHealth technologies and research conducted using mobile devices for health-related behavior, there are only few evaluation frameworks for assessing the usability of mHealth (Brown et al. 2013). Moreover, a lot of smartphone-based applications dedicated to diagnostic or disease treatment are developed and filled with content without the involvement of healthcare professionals, resulting in potentially incorrect health information, which in special cases might be even harmful for the end-users (Sedrati et al. 2016). For instance, among variety of applications available for patients with chronic respiratory disease only few were developed by, or jointly with medical professionals (Sleurs et al. 2019). Information collected by mHealth systems – whether psychological, behavioral or medical – is sensitive and highly personal, which raises the question of data security as well as integrity of the service provider when storing and processing recorded data (Kotz et al. 2016). Bad experience with mHealth technology, as well as perceived risks associated with its use are substantial inhibitors of its acceptance (Cocosila 2013; Matthew-Maich et al. 2016). Kotz et al. (2016) outline that the benefits of mobile health can be only achieved if end-users are confident in the privacy of their health-related data and if scholars collecting information are confident in preciseness and integrity of the data collected (Kotz et al. 2016).

5.4.Limitations and suggestions for future research

Although the present study was carefully designed with respect to the actual state of research and has provided some theoretical and practical contributions, it has several noteworthy shortcomings. Empirical data used for hypothesis testing was collected on a single point of time not considering the timely progress in opinion changing process. An experimental trial using a functional prototype of a pollen application could help to understand how the use of pollen applications influences health-related behavior during a pollen season and to which extent a pollen application can be considered a helpful tool in allergy management.

The present survey was conducted only in Germany without considering the cultural specifics or the level of technological development of this country. Most importantly, respondents recruited in the social media groups addressed to allergic subjects represent a convenient sample. On one hand, the data collected might be more realistic compared to acquiring the data from one location, especially using students as study participants. On other hand, people enrolled in self-help groups might have certain personality traits, such as high motivation in allergy coping, high degree of self-efficacy or need for social support. However, due to descriptive data, there are no reasons to believe the study participants differ from general population in terms of using IT technologies in general, or mHealth solutions for pollen allergy management in particular.

The scenario offered in the present study was of a static nature, not allowing the potential users to interact and fully test its utility as a pollen application in allergy management. This might induce a certain degree of bias since the pollen allergy sufferers faced a hypothetical situation. However, the use of scenarios is not uncommon in information system research (Hertzum 2003). Moreover, the scenario-based approach offers the advantage of predicting future trends and testing an idea in a highly sensitive field such as healthcare before developing a real mobile-based application.

The last noteworthy shortcoming of the present study is the use of a single-item scale construct measuring the actual utilization of pollen applications. In general, it is not recommended to use a single indicator due to reduced predictive validity in comparison to multi-item scale (Diamantopoulos et al. 2012). However, in many cases one indicator is sufficient, especially if specific conditions are given (Hayduk and Littvay 2012). In the present study, it was assumed that the use or non-use of pollen applications is a distinctive state. Due to this reasoning, the use of a single-item scale inquiring the utilization of pollen applications is a reasonable choice.

6. Conclusion

Overall, this study is one of the first empirical investigations on the role of different influencing variables on acceptance of pollen applications by pollen allergy sufferers. This research has demonstrated several key drivers facilitating the positive attitude toward pollen application use resulting in a development of a behavioral intention toward its use. The study shows the acceptance of pollen applications to be predetermined primarily by the perceived ease of use and the perceived usefulness of this mHealth solution. Representing a cognitive response to design features and implemented functionality of a technology, the both mentioned variables can be influenced by the way a pollen application is conceptualized and designed. Consequently, a special focus on implementation of the desirable features can facilitate the adoption behavior of allergic subjects. However, only satisfying the health purpose of a pollen application by providing high quality pollen information can be considered as a beneficial strategy fostering its sustained use.

By providing a theoretical model and empirical evidences in the present study, it is shown how interdisciplinary research can facilitate the development of IT solutions successful among its target population. In addition, the findings highlight enormous research potential at the intersection of different disciplines, such as information systems and healthcare.

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5.4 Contribution 4: Forecasting tomorrow's Betula and Poaceae airborne pollen concentrations on a 3-hourly resolution in Augsburg, Germany: towards automatically generated, real-time predictions

Muzalyova A, Brunner JO, Traidl-Hoffmann C, Damialis A (2020)

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Abstract: Airborne allergenic pollen impact the health of a great part of the global population.Under climate change conditions, the abundance of airborne pollen has been rising dramatically and so is the effect on sensitized individuals. The first line of allergy management is allergen avoidance, which, to date, is by rule achieved via forecasting of daily pollen concentrations. The aim of this study was to elaborate on 3-hourly predictive models, the first to the best of our knowledge, attempting to forecast tomorrow's pollen concentration, based on near-real-time automatic pollen measurements. The study was conducted in Augsburg, Germany, for four years (2016-2019) focusing on Betula and Poaceae pollen, the most abundant and allergenic in temperate climates. ARIMA and dynamic regression models were employed, as well as machine learning techniques, viz. artificial neural networks and neural network autoregression models. Air temperature, relative humidity, precipitation, air pressure, sunshine duration, diffuse radiation and wind speed were additionally considered for the development of the models. It was found that air temperature and precipitation were the most significant variables for the prediction of airborne pollen concentrations. Developed forecasting models performed well showing their ability to explain most of the variability of pollen concentrations for both examined allergenic species. However, predictive power of Betula forecasting model was higher achieving R 2 up to 0.62, whereas Poaceae up to 0.55. Neural autoregression was superior in forecasting Betula pollen concentrations, whereas, for Poaceae, seasonal ARIMA performed best. The good performance of seasonal ARIMA in describing variability of pollen concentrations of both examined taxa suggest an important role of plants' phenology in observed pollen abundance. The present study provides new insight on per-hour forecasts to be used in real-time mobile apps by pollen allergic patients. Despite the huge need for real-time, short-term predictions for everyday clinical practice, extreme weather events, because of climate change, still comprise an obstacle towards highly performing forecasts at such fine timescales, highlighting that there is still a way to go to this direction.

Keywords: Bioaerosols; Diurnal pollen distribution; Dynamic regression; Environmental health; Neural networks; Time series analysis

Introduction

Airborne pollen dispersion is part of plant phenology, following yearly seasonal cycles with the aim of successful reproduction. Whilst elementary for the ecosystem, pollen grains are known to be a trigger for allergic reaction in sensitized individuals (Sofiev and Bergmann 2013). The current prevalence of allergic diseases worldwide remains high, ranging from 15 to 25% (Passali et al. 2018), with industrialized countries affected more by this negative trend (Pawankar 2014). The ongoing increase in air temperature and the overall effect of climate change have been increasing steadily the abundances of airborne pollen across the globe, and, at the same time, have been shifting earlier the pollen seasons for several allergenic taxa (Ziska et al. 2019). The World Allergy Organization has warned that because of climate change plants will be stressed to flower and pollinate earlier within the year and in higher amounts, thus increasing the natural pollen exposure of sensitized individuals and, consequently, increasing the severity of associated symptoms (Pawankar 2014).

Being mostly not a life-threatening condition, pollen allergic symptoms can significantly reduce health-related quality of life and workplace productivity of people concerned because of profound physical and psychological complications (Blaiss et al. 2018; Haanpää et al. 2018; Devillier et al. 2016). Allergic individuals have several possibilities to control allergic symptoms with allergen avoidance being one of the most effective measures in relieving allergic symptoms (Glacy et al. 2013). However, since severity of occurring symptoms significantly depends on the current concentration of aeroallergens in the ambient environment (Bastl et al. 2013), to be effective, allergen avoidance strategies make sense only if performed when concentration of airborne allergenic pollen is high. Consequently, pollen information provided for example via pollen applications to the target population of allergic individuals, might become an important aid in avoiding exposure to allergenic pollen, and planning medication and outdoor activities (Kmenta et al. 2014). As airborne pollen has been identified as a biological weather parameter, a network of nearly 400 Hirst-type pollen traps is currently monitoring the airborne pollen in Europe (Berger et al. 2013). However, for pollen information to be useful for allergy management, it has to be delivered on time, shortly after the measurement took place, to reflect the actual pollen abundance. Therefore, in order to provide up-to-date information on pollen concentration a more rapid, and preferably instantaneous technique in pollen monitoring than a conventional pollen trap of Hirst-type, is needed. Automated pollen monitoring in real time might be a solution covering this urgent need.

Bavaria has developed a network based on the automatic pollen monitoring devices of BAA500 type (Bio Aerosol Analyzer 500) (Oteros et al. 2019), as described in more technical detail in (Oteros et al. 2015). The BAA 500 is an automatic system for air particle collection (among others, pollen and fungal spores), analysis, and automatic data transmission to a data bank, with pollen information available three hours after observation. Automatic pollen monitoring is a promising tool in pollen season monitoring, as it provides pollen information nearly up-to-date with a high sampling rate of up to 8 pollen measurements per day. The BAA 500 operated in Munich, Germany, was reported to be a functional pollen monitoring device with 93.3% of pollen automatically classified by that device to be correctly identified (Oteros et al. 2015). Automatic pollen monitoring is a new technique, which is yet not widely used. At the moment, only few countries stand out developing innovative monitoring sites. Among those are Japan (Kawashima et al. 2017), the USA (Buters et al. 2018), Switzerland (Crouzy et al. 2016), and Germany, the latter of which has been operating automatic pollen monitors for the last half decade.

The circadian pathophysiology of pollen allergy is well documented already (Nakao, Nakamura and Shibata 2015), with symptoms worsening over night or in the early morning. Because of the lack of real-time, high-resolution (hourly) pollen measurements, this phenomenon remains poorly researched. Most commonly, aerobiologists work on daily data, predicting the pollen concentration for the next day or several days ahead. The novel automatic pollen monitoring devices, with the near-real-time pollen data, allow to go beyond the current state-of-the-art and to develop reliable short-term pollen predictions. Pollen forecasting at this scale can be the cornerstone of operational diurnal allergy risk alerts for allergic individuals.

To achieve such operational forecasts, apart from the real-time, high-resolution pollen data, sophisticated mathematical and statistical tools need to be employed. Scientific works examining the diurnal pollen variation in the air only seldom apply deterministic predictive models, narrowing their efforts down to descriptive methods and correlation analysis (Ščevková et al. 2015; Fernández-Rodríguez et al. 2014; Chappuis et al. 2020). The most common predictive techniques used so far are linear or non-linear regressions, with significant steps having been made the last few years (Nowosad et al. 2018; Ritenberga et al. 2016; Piotrowska 2012), and time-series analysis, based on Box-Jenkins methods (García-Mozo et al. 2014; Ocana-Peinado, Valderrama and Aguilera 2008; Valencia et al. 2019). Also, variables like meteorological factors are frequently considered, as they have been proven as significant predictors of airborne pollen concentrations. Meteorological factors, such as solar radiation (Nowosad et al. 2018; Iglesias-Otero et al. 2015), sunshine duration (Myszkowska and Majewska 2014; Rodríguez-Rajo et al. 2006), and air temperature (Ščevková et al. 2015; Nowosad et al. 2018; Howard and Levetin 2014) are positively correlated with airborne pollen concentrations, whereas variables like relative humidity (Ščevková et al. 2015, 2015; Makra et al. 2011), and precipitation (Piotrowska 2012; Rodríguez-Rajo et al. 2006) show a negative association with airborne pollen abundances. Some papers examined the relationship between wind direction and wind speed, and found them to be of significant influence (Astray et al. 2010).

Nowadays, novel and more sophisticated forecasting techniques are starting to be employed, as in the case of machine learning, which is increasingly gaining scientific interest. Several aerobiological studies have implemented machine learning algorithms, at various scales of analysis, such as artificial neural networks (Valencia et al. 2019; Iglesias-Otero et al. 2015; Puc 2012), random forests (Nowosad et al. 2018; Zewdie et al. 2019), and support vector machines (Zewdie et al. 2019).

Each pollen forecasting technique exhibits pros and cons and their selection is based on the research question per case and on data availability and quality. Therefore, regression analysis allows for inclusion of co-factors, but neglects the serial autocorrelation of all variables. On the contrary, Box-Jenkins models consider the autocorrelation of the dependent variable, but neglect the effect of other potential co-factors. Dynamic regression, albeit a statistical approach using the advantages of both above-mentioned forecasting techniques (Pankratz 2012), has been seldom adopted in airborne pollen forecasting (Ocana-Peinado, Valderrama and Aguilera 2008). Overall, forecasting of pollen concentrations is challenging due to the data complexity, intense seasonality with numerous 'out of season' zero values, high skewness and level of irregularity and extreme outliers. The above are mixed in a double-periodic pattern, within-day and within-year, with different factors influencing each periodicity and pollen distribution. The relationships are often nonlinear and the affecting co-factors usually collinear and sometimes confounding. This challenge could be answered by machine learning algorithms, like artificial neural networks, as they have a high ability to assess complex relationships (Twomey and Smith 1995). To ensure the sound interpretation of the acquired results produced by the artificial neural network, it then makes sense to cross-validate the model output with that of 'conventional' forecasting techniques, as time series analysis and dynamic regression.

The aim of the present study was to assess and forecast the diurnal variability of airborne pollen concentrations and the development of short-term predictive models for the next day using near-real-time 3-hourly Betula and Poaceae pollen data. Both pollen taxa were selected because of their high atmospheric abundance in Bavaria (Oteros et al. 2019), and of their high prevalence in sensitization rates among the study area population (Muzalyova et al. 2019). To our best of knowledge, there is so far no research focusing on forecasting of diurnal pollen concentrations based on data provided by automatic pollen measurement systems of any kind. Therefore, this is the first paper using a 3-hour sampling frequency of airborne pollen detected by an automatic pollen monitoring to develop predictive models. Knowledge of variation of pollen quantity on hourly-scale is very important for people suffering from pollen allergies, as it can help them to avoid exposure to allergenic pollen. Incorporating real-time, automatic pollen measurements in airborne pollen forecasts is expected to dramatically improve the efficiency of allergy management.

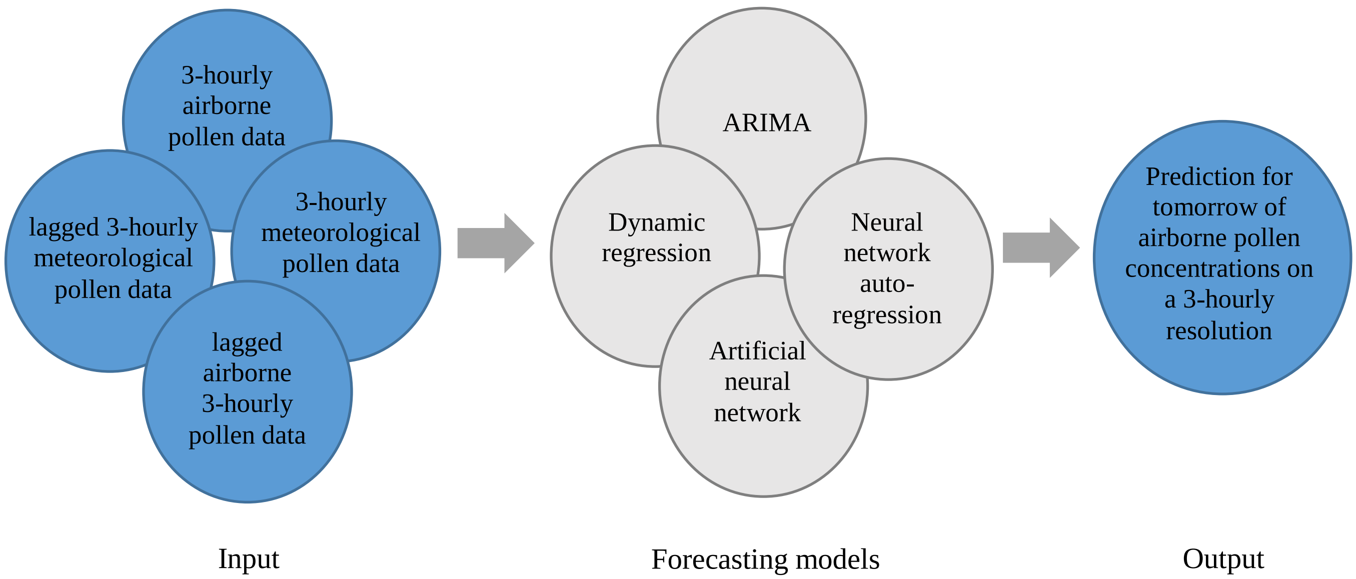


Figure 1: Processflow of the forecasting model development based on 3-hourly scale of data

Materials and methods

Data

Pollen data for *Betula and* Poaceae were acquired by use of an automatic pollen monitoring device BAA500, located in Augsburg, Germany. The automatic pollen monitor is located on the rooftop of the Bavarian State Office for the Environment (B*ayerisches Landesamt für Umwelt – LFU Bayern*) (coordinates 48°32'60.29''N, 10°90'30.77''E), located in a suburban environment in Augsburg, Germany. The pollen data were collected in 3-hour intervals for the years 2016 to 2019. Accordingly, each day (24-h period) encompasses 8 data points beginning with the first pollen measurement performed at midnight (0.p.m), and the last performed at 9 p.m. Pollen concentrations are expressed in grains per m^3 with a time step *n* corresponding to a 3-hour interval. Missing data (8.4% *Betula* and 7.8% Poaceae) were imputed based on regression analysis using 5 data points of the corresponding time period before and after the data gap. Scattered missing points were imputed by averaging closest measurement before and after the data gap. The normal distribution of the data was tested using the Kolmogorov-Smirnov and Shapiro-Wilk tests, where it was concluded that the hourly data did not follow a normal distribution being extremely right-skewed (Table 1).

Table 1: Descriptive statistics of the pollen measurements of examined taxa

	Betula	Poaceae
Mean (SD)	71.9 (138.1)	12.6 (29.7)
Median	30.0	4.0
Min	0	0
Max	1582.0	750.0
Skewness	5.9	10.0
Kurtosis	49.1	181.9

Meteorological data were retrieved from the German Weather Institute (*Deutscher Wetterdienst – DWD*, https://opendata.dwd.de/climate_environment/CDC/), recorded at the airport of Augsburg (coordinates 48°21'57.564" N, 10° 53'34.944" E), located approximately 11km north of LFU. The following meteorological parameters were available for data analysis: air temperature [°C], relative humidity [%], air pressure [hPA], precipitation [mm], sunshine duration [min], solar radiation [J/cm^2] and wind speed [m/s]. A Spearman correlation test was used to analyze associations between the examined meteorological variables. The statistical analysis included the 3-hourly data set from March to September (main pollen season of *Betula* and Poaceae) and was performed with the SPSS 25.0 statistical package.

The analysis of the diurnal distribution of pollen concentrations and development of predictive models were performed based on pollen data of the main pollen season for each pollen taxa and each year. Accordingly, the following phenological features were determined for each available study year: Pollen Season Start (PSS), Peak Date (PD), Pollen Season End (PSE), Pollen Season Duration (PSD), and the annual Pollen Index (PI). The PSS was defined in line with European Aeroallergen Network pollen season definition. Due to this, the PSS was the first day achieving 5% of the cumulative average daily pollen counts over the whole year. The PSE was determined as a day reaching 95% of the cumulated average daily pollen counts throughout the whole pollen season (Bastl, Kmenta and Berger 2018). The PI was specified as the sum of the daily average pollen counts per cubic meter over the whole year. The PD was defined as the day with the highest daily pollen count.

Nomenclature

ω: periodic term	Θ: parameter of seasonal moving average model
B: difference operator	η: error term following ARIMA process
d: non-seasonal difference	*f:* activation function
p: order of the non-seasonal autoregressive model	*x:* input of a neural network
q: order of the non-seasonal moving average model	*y:* output of a neural network
P: order of the seasonal autoregressive model	*w:* weight of a neural network structure
Q: order of the seasonal moving average model	*b:* bias
φ: parameter of non-seasonal autoregressive model	*MAE:* mean average error
θ: parameter of non-seasonal moving average model	*RMSE:* root mean square error
Φ: parameter of seasonal autoregressive model	R^2: coefficient of determination

Autoregressive integrated moving average (ARIMA)

ARMA or ARIMA (also known as Box-Jenkins model) represent a combination of autoregressive and moving average models (Box et al. 2016). For modeling of seasonal time series, ARIMA(p, d, q)(P, D, Q)$_\omega$ is known as multiplicative ARIMA model (Cowpertwait and Metcalfe 2009). Due to this, six parameters, namely *p, d, q, P, D,* and *Q,* have to be determined to be included in the forecasting model. This step was performed based on the analysis of the Partial Auto Correlation Function (PACF) and Auto Correlation Function (ACF). The Akaike Information Criteria (AIC) and the Bayesian Information Criterion (BIC) were the adjustment criteria used for selection of the best model for each examined pollen specie. Additional confidence in the best fitting model was gained by deliberately overfitting the model by including further parameters and observing increase in the AIC and BIC. After the best fitting model was found, the correlogram of the residuals was verified as white noise.

Dynamic Regression (DR)

A dynamic regression is an extension of a regression model allowing errors from the regression to contain autocorrelations (Pankratz 2012). A dynamic regression uses advantages of the Box-Jenkins method modelling the autoregression between successive observations of the time series, and allows for the inclusion of the external influencing variables like a conventional regression. Additionally, dynamic regression can be applied to seasonal data, (Harvey and Scott 1994) and also allows for lagged effect of the predictors (Pankratz 2012). In the present study, the order of the autoregressive and moving average components for the dynamic regression modelling was determined based on the evaluation of the PACF and ACF. The external predictors were selected based on backward elimination using Julian day, and 16 lags of each available meteorological variable. Similar to ARIMA, AIC and BIC were used as adjustment criteria for the best fitting model along with the significance of the selected parameters.

Artificial Neural Network (ANN)

Artificial neural networks are forecasting methods based on a simple mathematical model inspired by information flow in the human brain. A neural network consists of a system of artificial neurons organized in layers. A common neural network incorporates an input, an output layer, as well as one or several intermediate layers containing so-called hidden neurons. A network can incorporate one to many hidden layers, and one to many neurons in each. The number of input neurons is defined by the number of used input features, and the number of output neurons is defined by the number of required output. The idea of a neural network is to model the response variable, representing the output, based on nonlinear combination of several input variables. A neuron receives information from other neuron or from an external influencing variable and computes a function *f* based on the weighted sum of the inputs (Goodfellow, Bengio and Courville 2016). The output of a neural network structure having three neurons in the hidden layer shown in Figure 2 where $x_j$represents the input, w_{ij} is the weight from neuron *j* to neuron *i*, and *b* denotes bias. The function *f* represents an activation function which determines the output activity of the neuron. Through the activation function the neuron and, thus, the model maps from a linear input to a non-linear output. Neural network development requires a big implementation of models with different number of neurons in the hidden layer. Designing an optimal schema involves finding the structure with the smallest size network (parsimonious network), which produces optimal errors for trained as well as untrained cases (Astray et al. 2016). During the training phase of the model development, bias values and weights are modified to minimize the error between outputs produced by the model and target values using Mean Squared Error Loss function for linear problems, as given in the preset study.

In the present study, the Julian day of the measurement and available meteorological variables with up to 16 lags of each (up to two-day delay-effect) were used as input variables for the neural networks developed. As the pollen data are usually strongly autocorrelated, the pollen concentrations detected in the previous time periods reflect this time series and were included as influencing variables in order to improve the prediction capacity of the neural network. Since, measurements of available input parameters were made on different scales, the parameter were normalized to lie between 0 and 1 before being imputed to the neural network.

Neural Network Autoregression (NNAR)

Neural network autoregression has a similar theoretical foundation as the ANN explained above. However, this type of an artificial neural network was specifically developed for autoregressive time series and represents a hybrid architecture comprising an ARIMA model and a neural network (Hyndman and Athanasopoulos 2018). Those combined methods are argued to give better forecasts by taking advantage of each model's capability (Taskaya-Temizel and Casey 2005). Due to its neural network part of architecture it is capable of estimating non-linear relationships, and due to its underlying ARIMA part, the algorithm explicitly uses lagged values of the time series as inputs.

A neural network autoregression is denoted as NNAR (*p*, *P*, *k*) with *p* indicating the number of lagged inputs, *P* indicating the number of seasonal lagged inputs, and *k* representing nodes in the hidden layer. For example, an NNAR $(2, 1, 3)_8$ uses inputs y_{t-1}, y_{t-2}, and y_{t-8}, has three neuron in the hidden layer and is complementary to ARIMA $(2,0,0)(1,0,0)_8$ but without the restriction on the parameters that ensure stationarity.

In the present pollen study, the order of p and P was determined based on the PACF analysis with Julian day and meteorological variables used as external influencing variables similar to the deployment of the ANN. The number of neurons in hidden layer was established similar to the ANN by a trial and error process based on the prediction accuracy of several tested models.

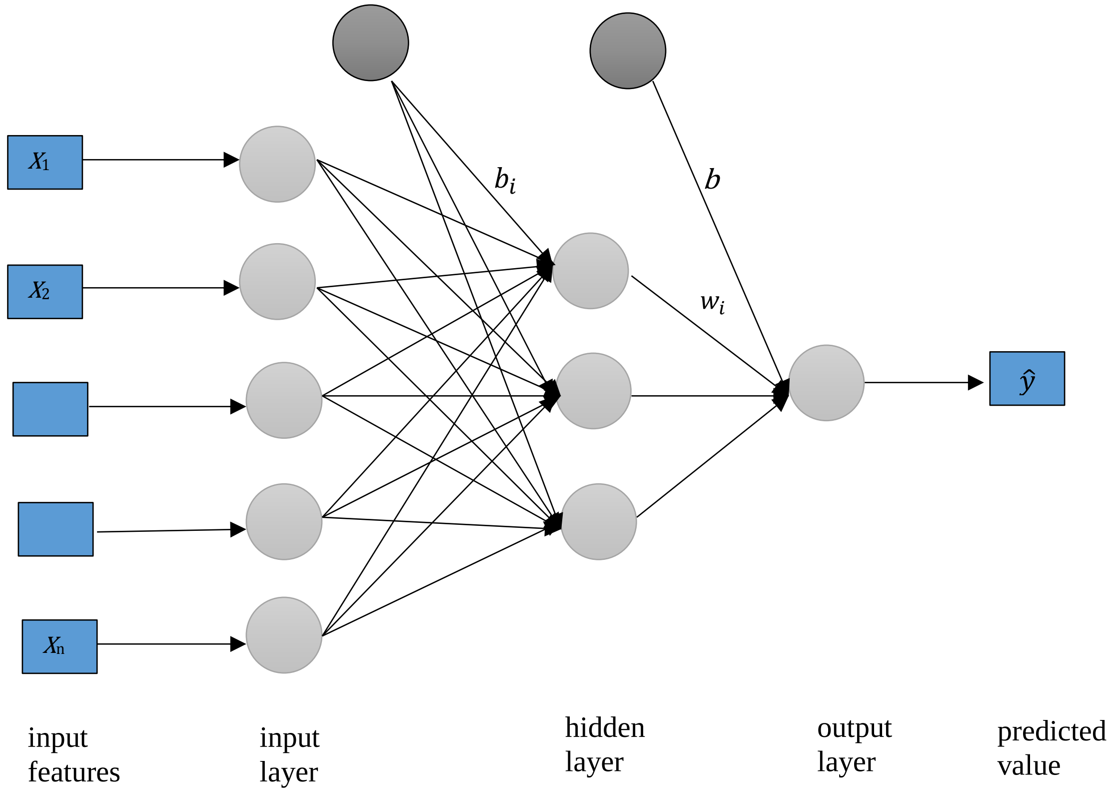


Figure 2: Neural network structure with 3 hidden neurons

Model validation

It is a common practice in the data modelling to test the predictive power of the established forecasting models on unknown data, not deployed for the fitting process (Goodfellow, Bengio and Courville 2016). For this purpose, the available pollen dataset was split into a training and test datasets as following: the dataset representing the main pollen season in the last year, 2019, was used for the test of the developed predictive models, and the remaining three years of pollen data were applied for the model fitting and training. The predictive accuracy and validity of each established forecasting model was determined based on the comparison of predicted and observed pollen concentration values. Two accuracy metrics, namely mean absolute error (*MAE*) and root mean squared error (*RMSE*) were used as criteria for evaluation of the performance of the established forecasting models:

$$MAE = \frac{\sum_{i=1}^{N} |\hat{y}_i - y_i|}{N} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}{N}} \quad (2)$$

Generally, the RMSE stronger punishes deviation between predicted value $\hat{y}_n$ and observed variable y_n due to squaring the difference. It is therefore better suited for modelling on data with strong peak and outliers (Twomey and Smith 1995).

As both introduced accuracy metrics are based only on error term e_t, they are therefore scale-dependent and allow to make comparison between time series that involve different units. In order to compare the performance of predictive models based on pollen data of *Betula* and Poaceae, the coefficient of determination (R^2) was used. R^2 describes the proportion of variance explained by the model to the total variance in the data, and can be defined using the following formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

All forecasting techniques were implemented in RStudio, version 1.0.143 using *tseries*, *fpp2*, *lmtest*, *neuralner* libraries.

Results

The characteristics of the examined pollen seasons are outlined in Table 2. The main pollen season of *Betula* started by the end of March (from 15/03 to 8/04), and lasted on average 38 days (SD = 10.2). The main pollen season of Poaceae started by the end of April (from 12/04 to 12/05), and had a comparably longer duration of 95 days (SD = 12.9). Considering *Betula*, the PD of the pollen season usually occurred shortly after the PSS on the 13th day of the main pollen season (from 04/04 to 14/04), whereas the PD of Poaceae was situated closer to the middle of the main pollen season and occurred on the 40th day (from 03/06 to 09/06) of the main pollen season. Furthermore, *Betula* usually had one well-defined peak, whereas Poaceae was characterized by several peaks of variable amplitude within the main pollen season. Generally, the pollen release of *Betula* was more intensive in absolute terms, peak values and also average pollen concentration per time period, compared to that of Poaceae.

Regarding inter-annual variability, the pollen season of the year 2018, interestingly, stands out among analyzed pollen seasons due to the earlier PSS and PSE for both investigated allergenic species (Table 2). In particular, the main pollen season of *Betula* started already by the beginning of April and lasted for more than fifty days. The PSS of Poaceae occurred 10 days earlier of the average date and ended by the middle of July. Furthermore, the intensity of the Poaceae pollen seasons were continuously decreasing across examined years, with 2019 exhibiting the lowest pollen abundance of all years (Figure 3).

Table 2: Descriptive statistics of the examined pollen seasons. The dates per season feature are provided, including the range in parenthesis.

	2016	2017	2018	2019	Average
Betula					
PSS	05/04	30/03	04/03	01/04	27/03 (15/03-8/04)
PSE	09/05	13/05	24/04	25/04	27/05 (19/05-04/06)
PSD	34	44	51	24	38 (10.2)
PI	20,014	13,967	4,363	15,679	13,510 (5720.204)
PD	12/04	01/04	16/04	09/04	09/04 (04/04-14/04)
Mean (SD)	73.3 (170.5)	87.0 (165.4)	41.6 (52.9)	77.5 (89.4)	71.9 (138.1)
Poaceae					
PSS	07/05	11/05	21/04	27/04	01/05 (13/04-13/05)
PSE	02/08	28/07	18/07	13/08	31/07 (22/07-09/08)
PSD	87	78	107	108	95 (12.9)
PI	16,772	11,938	6,552	3,126	9,597 (5,198.7)

PD	07/06	09/06	01/06	08/06	06/06 (03/06-09/06)
Mean (SD)	23.2 (48.5)	19.1 (31.7)	8.0 (15.1)	3.5 (5.7)	12.6 (29.7)

PSS: pollen season start, PSE: pollen season end, PSD: pollen season duration, PI; pollen index, PD: peak day, SD: standard deviation, (n): Julian day

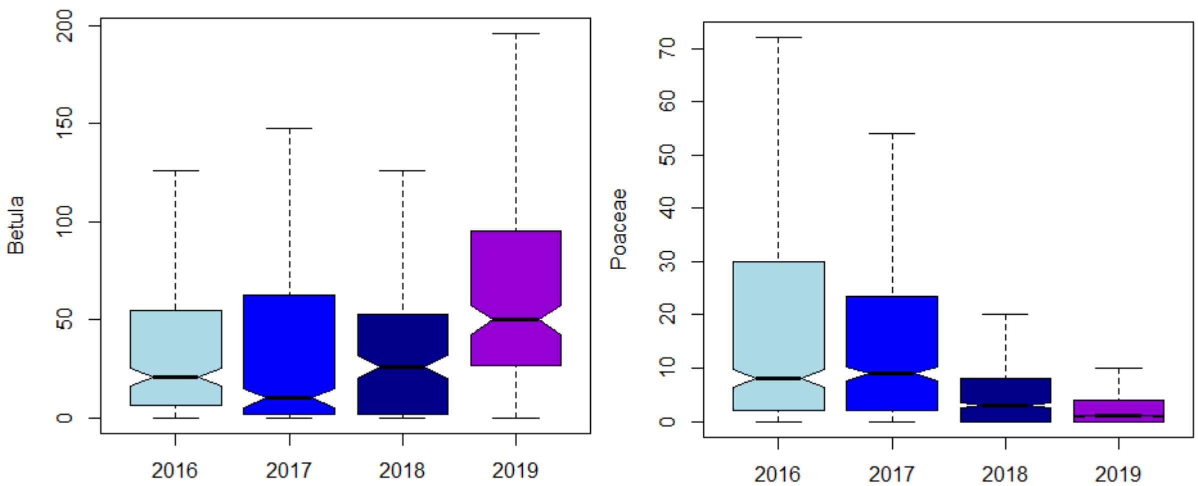


Figure 3: Boxplots of examined pollen taxa

The diurnal distribution of pollen concentrations of both taxa is depicted in Figure 4. The pollen load of *Betula* was relatively constant during the day with the highest levels occurring at 3 p.m. Kruskal-Wallis-Test revealed a significant difference between time periods (H (7) = 28.590, p < 0.01). However, due to high standard deviation and none well-defined diurnal patterns a posthoc test (Dunn-Bonferroni) revealed only difference between 12 a.m. and 3 p.m. to be significant (z = -3.137, p =0.048), whereas all other differences of pollen concentration between considered time periods were non-significant. On the contrary, the pollen concentration of Poaceae was noticeably peaking twice a day at 9 a.m. and 3 p.m., with relatively low abundance during the night hours. The Kruskal-Wallis-Test revealed a significant difference between groups (H (7) = 317.982, p < 0.01), and a pairwise comparison showed significant differences between pollen concentrations measured between the night hours and early morning (9 p.m. - 6 a.m.) and those observed beginning with morning until evening (9 a.m. – 6 p.m.). As pollen concentration of Poaceae is higher during the warmer parts of the day, it suggests a stronger relationship between airborne pollen concentrations of this allergenic species and warmth-related meteorological variables like air temperature, sunshine duration and solar radiation.

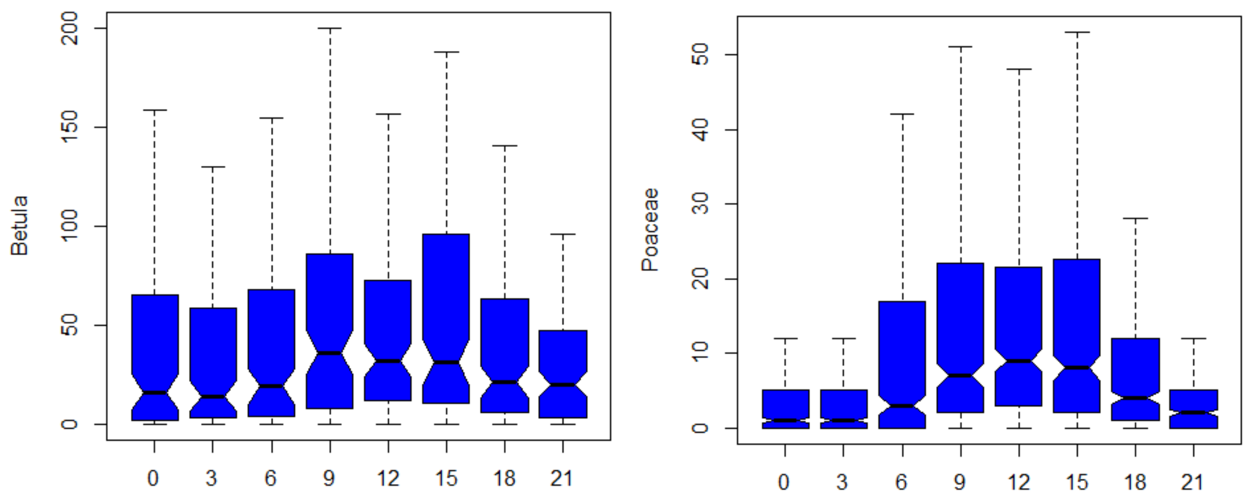


Figure 4: 3-hourly average distribution of Betula and Poaceae *pollen concentrations over 24 h*

Correlogram analysis (Figure 5) of *Betula* pollen concentrations showed a steady decrease with no well-defined peaks at daily cycle (at 8^{th} lags), concluding that a seasonal term has to be included in the model. Inspection of the PACF-correlogram suggested that choosing one non-seasonal, and none seasonal autoregressive and moving average parameters were sufficient. However, due to rising significant correlation between 5^{th} and 8^{th} lags in the PACF, up to seven non-seasonal autoregressive and moving average parameters were tested. Correlogram of the Poaceae pollen data depicts a tendency similar to *Betula*'s, including a well-defined seasonality of the data at 8^{th} lags, however, the decrease across the lags occurs considerably slower in comparison to *Betula*, presumably due to the shorter main pollen season duration. Inspection of the partial autocorrelation function showed a high significant correlation at lag one. According to this analysis one non-seasonal, as well as, up to two seasonal autoregressive and moving average parameters might be sufficient for the ARIMA model. However, in order to estimate the effect of overfitting up to seven, both, autoregressive and moving average parameters, and one seasonal autoregressive and moving average parameters were tested. The best fitting model for each pollen species was chosen based on the lowest AIC and BIC statistics.

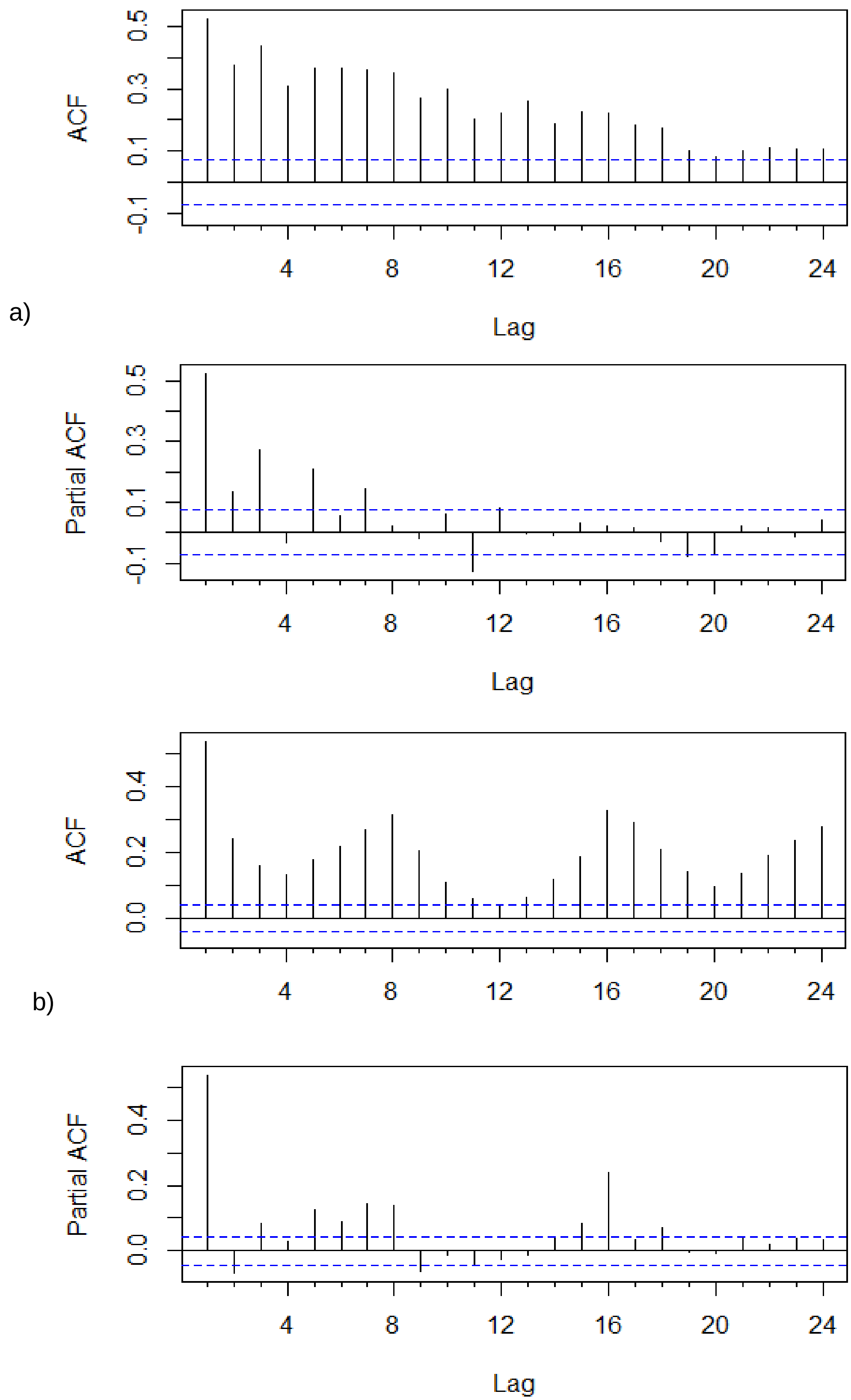
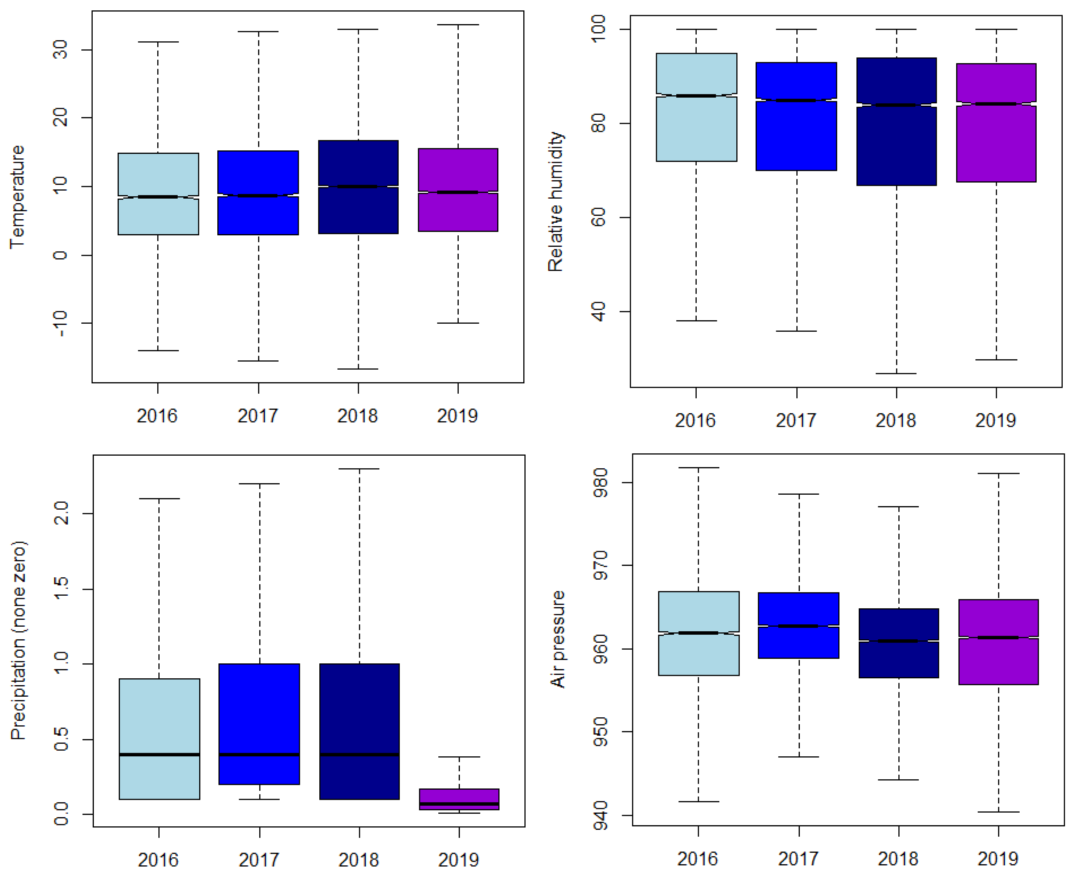


Figure 5: ACF and PACF for Betula (a) and Poaceae *(b) pollen data*

It is not possible to mention all relevant results of tested ARIMA model structures in this paper, therefore, the structures related singly to the best-fitted models are presented in the Table 3. Thus, the best ARIMA model of *Betula* pollen concentration corresponded to ARIMA $(7,1,3)(1,1,1)_{[8]}$, and contained seven non-seasonal autoregressive and three moving average parameter, and one of each seasonal autoregressive and moving average parameter. Regarding Poaceae, the best fitting model was given by ARIMA $(1,1,2)(1,0,1)_{[8]}$ and consisted of one non-seasonal autoregressive parameters, two non-seasonal moving average parameter, and one of each seasonal autoregressive and moving average parameter.



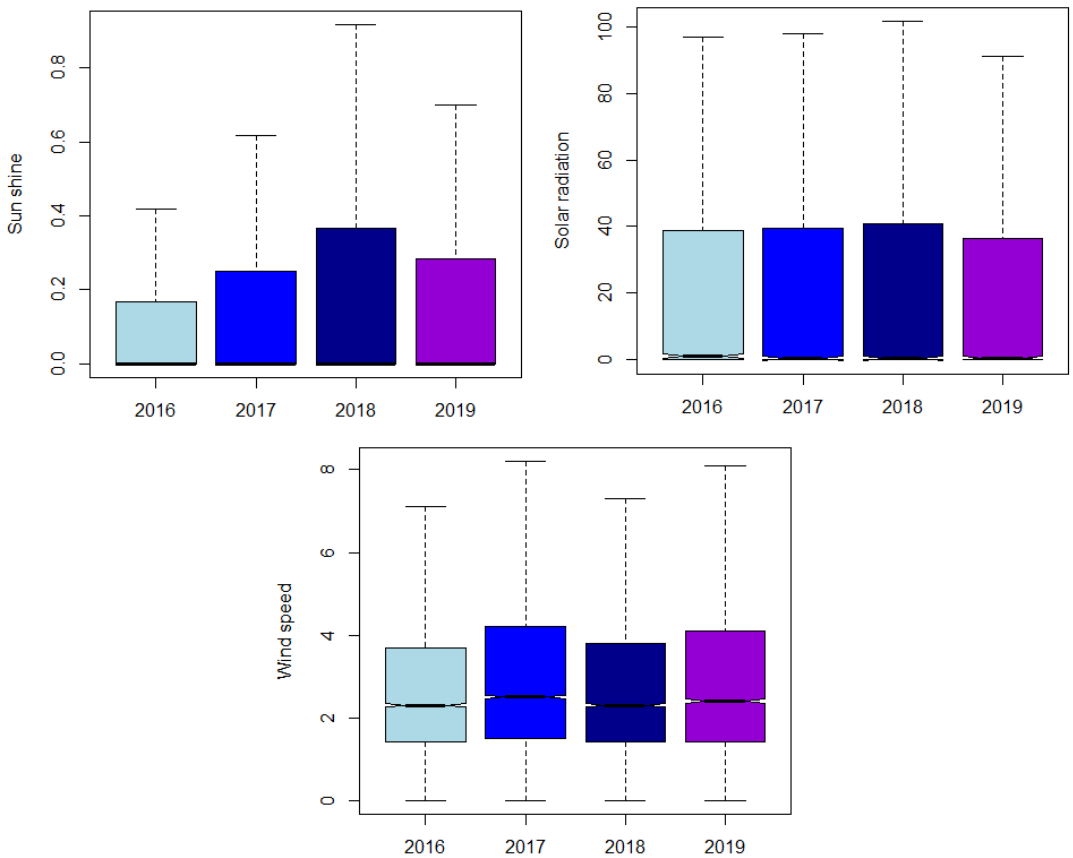


Figure 6: Comparison of examined meteorological variables per year

Descriptive analysis of the meteorological variables (Figure 6) reviled a significant difference between the years used in the training data set and the year 2019 representing the test data set. Particularly, the year 2019 was significantly drier in comparison to all other considered pollen seasons.

Table 3: Correlation coefficients of pollen concentrations and meteorological variables (only training dataset)

	T (°C)	RH (%)	P (mm)	AP(hPa)	WS (m/s)	S (min)	R(J/cm^2)
Betula	0.248**	-0.238***	-0.230***	0.163**	0.018	0.207**	0.208**
Poaceae	0.471**	-0.369**	-0.151**	0.002	0.079	0.370**	0.387**

T: temperature, RH: relative humidity, P: precipitation, AP: air pressure, WS: wind speed, S: sun shine, R: diffuse radiation

The Spearman's correlation analysis was used preliminary to DR development in order to discover relationships between pollen concentrations and available meteorological parameters. The results of correlation analysis are given in the Table 3. Generally, correlations were significant in a large number of cases. As expected, Poaceae pollen concentrations were strongly related to air temperature, sunshine, and solar radiation in comparison to *Betula* pollen counts. The air pressure was found to be significantly correlated only to *Betula*, whereas precipitation and humidity were negatively related to the pollen concentrations of both pollen taxa. No significant relationship between wind speed and pollen concentrations were detected.

The order of autoregressive and moving average parameters in DR was determined based on ACF and PCF analysis, however, with regard to previous ARIMA modelling. All available weather data were imputed in the dynamic regression using up to 16 lagged values representing two days as well as Julian day of the measurement and tested for significance. A step-by-step procedure was followed and a backward stepwise removal of all non-significant influencing variables was processed, beginning with the highest p-value. The best fitting model was determined using AIC and BIC values along with significance of the certain influencing variables. The final result depicting the best fitting model for both pollen taxa can be taken out of Table 4.

Similar to correlation analysis, air temperature had a positive significant effect on the airborne pollen concentrations for both examined pollen species, with regression coefficient being higher for *Betula*. However, multiple lagged time periods of temperature measurement were found significant for Poaceae, suggesting airborne pollen concentration of this species to be more sensitive to air temperature. Precipitation had a substantially greater impact on pollen abundance for both examined species reflected in higher calculated parameters with this effect lasting up to 6 hours. Interestingly, the effect of rain occurred immediately on *Betula* airborne pollen concentration and with a delay of three hours on Poaceae. The air pressure was a significant predictor but only for airborne *Betula* pollen. Furthermore, only examined meteorological variables representing at most 8^{th} lag were determined as significant predictors of the airborne pollen concentration suggesting that only most current values have an influence on the pollen levels in the air.

Table 4: Coefficients obtained for ARIMA and DR models

	ARIMA		DR	
	Betula	Poaceae	*Betula*	Poaceae
φ_1	-0.59***	0.24***	0.59***	0.18***
φ_2	-0.38***		-0.41***	
φ_3	0.53***		0.51***	
φ_4	0.10		0.07	
φ_5	0.26***		0.29***	
φ_6	0.09*		0.16***	
φ_7	0.25***		0.25***	
Φ_1	0.17***	0.92***	0.17***	0.88***
θ_1	0.03	-0.72***	-0.07***	-0.69***
θ_2	-0.29***	-0.26***	-0.23	-0.28***
θ_3	-0.74***		-0.84	
Θ_1	-1.00***	-0.80***	-1.00**	-0.75***
T			5.47**	2.31***
T_1				-0.97**
T_5				0.91***
T_8				-0.74**
P			-71.03***	
P_1			-39.20**	-2.77****
P_2			55.74***	-2.15***
AP			12.85**	
AP_1			-12.31**	
Ljung-Box test				
$Q^*(df)$	5.39(4)	48.21(11)	15.71(3)	59.19(15)
p-value	0.24	0.00	0.00	0.00
Goodness-of-fit				
R^2	0.42	0.38	0.46	0.42

Significance levels: 0.001 ***, 0.01 **, 0.05 *

Generally, extension of ARIMA model by meteorological variables has improved the performance of the predictive models in terms of higher coefficient of determination (R^2), however, this effect was small despite highly significant relationships.

Statistical results obtained from the ARIMA and DR analysis were used as a starting point for the setup of the both neural networks. Particularly, the best fitting order of the autoregressive parameters served as a starting framework for definition of the NNAR structure. Accordingly, for *Betula* NNAR structure was defined as NNAR $(7,1,k)_{[8]}$, and NNAR $(1,1,k)_{[8]}$ for Poaceae. Lagged pollen counts corresponding to the p and q order of the ARIMA model were also employed as input features in the ANN. All available meteorological variables including its lagged values were deployed as influencing variables in NNAR and ANN, as well as Julian day of the measurement. The number of neurons in the hidden layer k for each neural network was determined iteratively by testing different neuron schemas. After the trial-and-error process, structures providing better results in terms of the model accuracy were obtained for each of examined allergenic species, and each neural network used for data modelling. The final neuron structures, as well as, goodness-of-fit criteria can be taken out from the Table 5. Interestingly, the best NAAR structure for predicting *Betula* airborne pollen counts was given by one autoregressive non-seasonal component in comparison to ARIMA and DR having the order of 7. The most important meteorological variables for NNAR and ANN were Julian day, air temperature, precipitation and solar radiation, whereas the NNAR prediction of Poaceae pollen levels was dominated singly by precipitation. It is also remarkable, that neural networks predicting *Betula* pollen counts achieved substantially higher R^2 coefficients in training process in comparison to Poaceae.

Table 5: Neural networks schemas of fitted models

	Model	R^2
Betula	NNAR (1,1,8)	0.74
	ANN (13,6,1)	0.91
Poaceae	NNAR(1,1,4)	0.56
	ANN (12,8,1)	0.63

The predictive models fitted to the training data set were applied on the test data set in order to determine their predictive accuracy. Overall, the ARIMA and DR could achieve higher coefficients of determination in the test run in comparison to the training of the models. Furthermore, ARIMA and DR performed almost equally well, thus, the deployment of additional meteorological parameters have not changed the predictive accuracy significantly.

On the contrary, the high coefficient of determination achieved when fitting neural networks using training data, were only partly reproduced in the independent test. The goodness-of-fit of the independent model test can be seen in the Table 6. The NNAR produced better predictions for *Betula* whereas simple seasonal ARIMA outperformed all other predictive methods in forecasting airborne Poaceae pollen concentrations. Furthermore, DR exhibited low predictive power for Poaceae pollen levels. Despite substantially higher values of *RMSE* and *MAE,* forecasting models predicting *Betula* pollen concentrations performed better, achieving R^2 in the range between 0.13 and 0.62. On the contrary, predictive models of Poaceae achieved coefficients of determination between 0.03 and 0.55. The high *RMSE* and *MAE* for *Betula* pollen concentrations were predetermined by higher intensity of airborne pollen levels in comparison to Poaceae.

Table 6: Comparison of the prediction capabilities for one day ahead forecast

	Betula				Poaceae			
	ARIMA	DR	NNAR	ANN	ARIMA	DR	NNAR	ANN
RMSE	59.15	59.41	55.76	84.94	3.81	6.86	4.85	4.26
MAE	34.22	37.03	35.50	49.22	2.23	5.33	3.70	3.21
R^2	0.56	0.56	0.62	0.13	0.55	0.03	0.29	0.45

Figure 6 shows the comparison of predicted values based on four applied modelling techniques and observed *Betula* pollen concentrations. The test prediction was made using roughly 25% of the available data and consisted in total of 200 data points. The figure depicts predictions provided by each of the tested forecasting models. The black line shows the observed pollen counts for considered data points and the other lines depict prediction made by ARIMA, DR, NNAR, and ANN. As can be seen, *Betula* had no single well-defined peak in the test data set, and the highest pollen level was achieved closer to the middle of the pollen season. ARIMA, DR and NNAR caught this pollen behavior relatively well, even if strongly underestimating the peak value. On the contrary, the ANN missed the peak of the season completely and placed it several time periods after it actually occurred. Furthermore, it is noticeable that ANN tended either to strongly overestimate, or miss several peaks inside the season, whereas the NNAR generally captured this pollen behavior but underestimated it. Additionally, the DR also showed a tendency to slightly overestimate the airborne pollen concentrations.

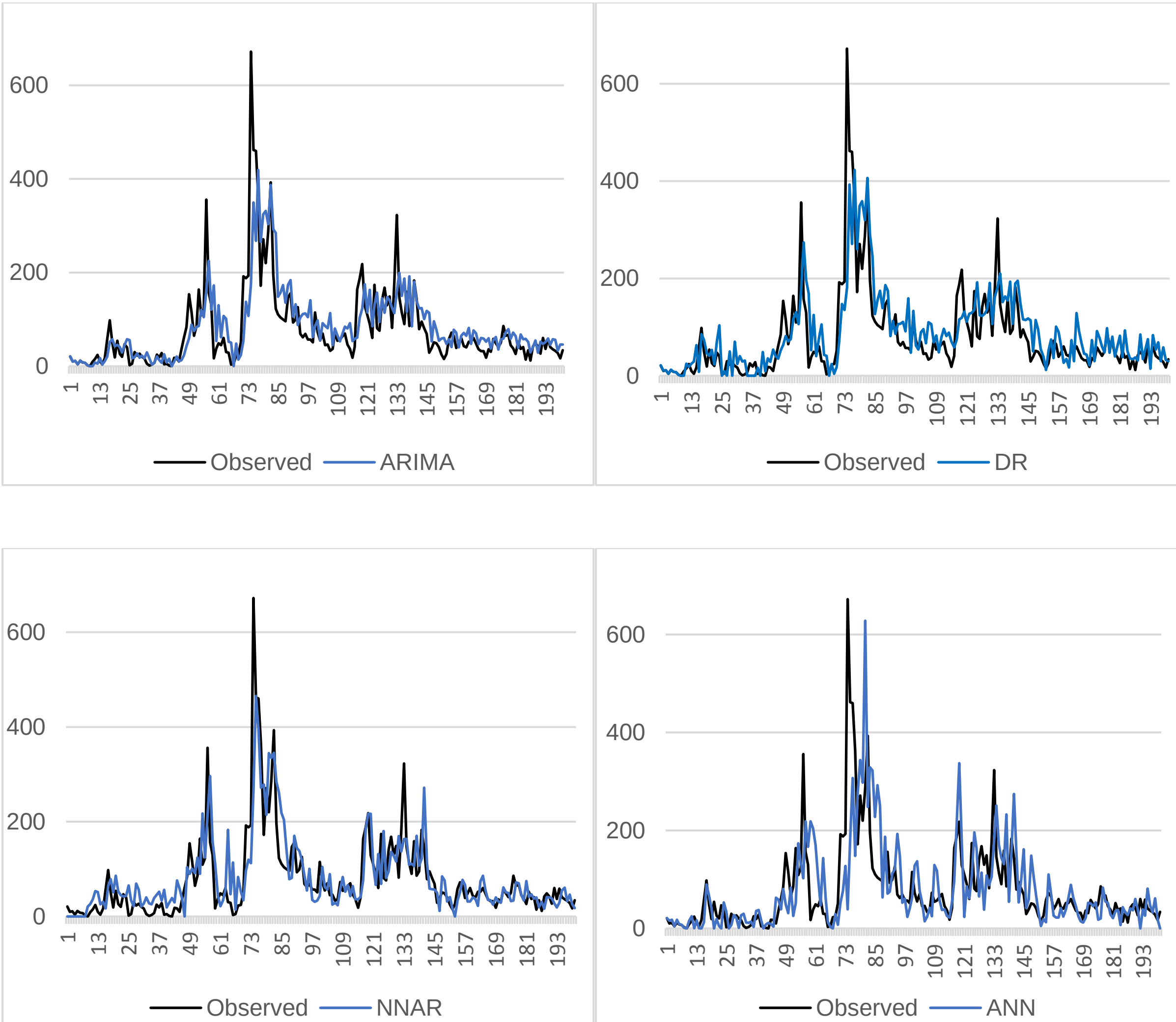


Figure 7: Results of independent test for Betula pollen data (3 hourly sequence) using 4 forecasting techniques

The test of the established predictive models for Poaceae pollen concentrations was performed using the main pollen season 2019 representing roughly one fourth of the data, and contained in total 872 data points. Figure 7 depicts a representative section of the observed pollen counts beginning with the start of the considered pollen season, and predicted values using four forecasting techniques. As shown in the graphical representation, the observed peaking behavior of pollen counts was overestimated by all applied forecasting techniques despite ARIMA. Additionally, DR showed a tendency to strongly overestimate the variability of the airborne pollen concentrations, whereas both neural networks predict values clearly above the actually observed pollen concentrations, however, capturing the pollen behavior in terms of its amplitude. This result can be traced back to the lowest intensity of the Poaceae pollen season among all examined pollen seasons. ARIMA describes well the pollen behavior of low pollen concentrations of low pollen levels, and the ANN outperformed in forecasting the peaking behavior beginning with the time period 169.

Overall, the direct comparison of the observed and calculated values using four forecasting techniques confirmed the good performance of the most developed predictive models, and the ability to recreate a significant amount of variation in the data for both examined allergenic species.

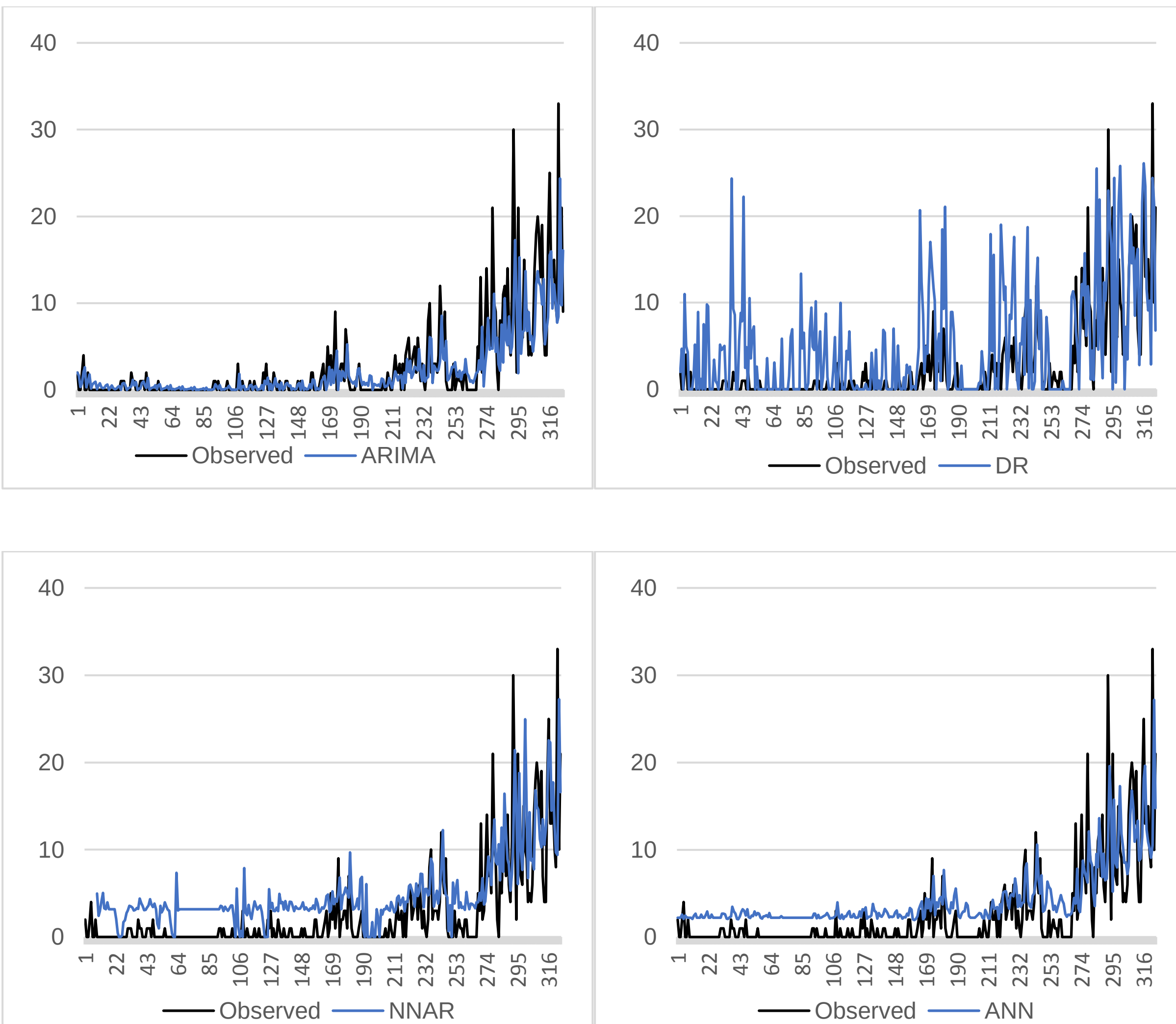


Figure 8: Results of independent test for Poaceae pollen data (3-hourly sequence) using 4 forecasting techniques

Discussion

In the present study, we elaborated novel, automated, near-real-time pollen data, on a 3-hourly time resolution, attempting to predict pollen concentrations on a diurnal horizon. To achieve this, we used a variety of statistical techniques, among which time series analysis and machine learning. Most forecasting attempts have been using much simpler tools or less fine time resolution. From an operational and clinical point of view, allergic patients and their practitioners actually need the diurnal distribution of air pollen abundances every day so as to plan their daily activities, including exposing (or not) themselves to expected airborne pollen concentrations and receiving the appropriate medication.

Considering that sensitization rates to airborne pollen account up to 25% worldwide (Passali et al. 2018), and pollen allergies comprise according to the World Allergy Organization one of the emerging diseases of the century (Pawankar 2014), the abovementioned information will undoubtedly be the cornerstone for the pollen allergen avoidance on a regular basis, if disseminated operationally. Specifically in the study area's country, Germany, almost 15% of adult population are suffering from at least one allergic disorder (Bergmann, Heinrich and Niemann 2016, 2016), and allergic individuals account for about 12.6 % among German children (Schmitz et al. 2014). This additionally highlights the necessity for the elaboration of such prophylaxis and management toolkits.

This study employed advanced statistical methods, namely ARIMA, dynamic regression and machine learning, such as neural autoregression and artificial neural network, to predict pollen concentrations of *Betula* and Poaceae in Augsburg, Germany. The mathematical modelling techniques were used in combination with meteorological factors and past pollen observations in order to make a prediction of expected pollen levels one day ahead on a 3-hourly scale. Such approaches are quite common in this research area, nonetheless, usually on a coarser timescale.

Among the statistical forecasting techniques employed in the present study, dynamic regression, considered autocorrelations both with the dependent pollen data and the values of meteorological variables, and performed better in pollen prediction based on the training dataset. This finding agrees with Sanchez and Galan (2005), who showed the combination of meteorological factors and previous pollen data to yield better results in pollen forecasting, than using alone pollen data or meteorological variables (Sánchez Mesa, Galán and Hervás 2005). In the present study two meteorological variables, namely air temperature and precipitation were determined as significant predictors in DR modelling for both examined pollen species, with precipitation having a stronger effect on the airborne pollen concentration. In the current aerobiological research, the most of pollen forecasting studies apply some meteorological variables as input parameters. Among them, air temperature is one of the most studied meteorological factors which is discovered to have a significant effect on airborne pollen concentrations across different pollen taxa (García-Mozo et al. 2014; Ziello et al. 2012). For example Howard and Levetin (2014) used air temperature and precipitation to predict pollen concentrations too (Howard and Levetin 2014), discovering that temperature was one of the most significant repressor. Iglesias-Otero et al. (2015) employed precipitation, sunshine duration, and humidity, with rainfall being the most sensitive variable in the predictive model (Iglesias-Otero et al. 2015). These findings agree with our result, showing the precipitation to have an even stronger impact on airborne pollen levels. That suggests that rainfall simply washes out the pollen grains from the air with this effect lasting for several hours. It is worth pointing out here that different meteorological and climatic indices would provide variable predictive capacity to our developed models, and this is highly relying on the timescale examined. It is well known, as documented i.e. by Damialis et al. (2005) that even by conventional Hirst-type monitoring techniques, wind vectors and precipitation are the leading determining factors, with the effects lasting for at least four hours (Damialis et al. 2005). In the present study, although an extension of the simple ARIMA model by meteorological variables provided better results in the training, the predictive power of ARIMA and DR models were similar for *Betula* pollen counts, whereas DR failed in predicting airborne pollen concentration of Poaceae, achieving coefficient of determination of R^2 = 0.03. Furthermore, considering Poaceae pollen counts, the simplest among applied forecasting techniques, namely ARIMA, clearly outperformed all other models.

Regarding the two machine learning techniques used for the development of predictive models, neural autoregression substantially outperformed the artificial neural network, for *Betula* pollen data, and delivered the best predictive power in terms of R^2 of all applied forecasting techniques. On contrary, Poaceae was better predicted by ANN. In general, the forecasting model developed for *Betula* pollen performed better in terms of obtained coefficient of determination R^2 in independent test, despite higher variation in the data. Possibly, it can be explained by a shorter main pollen season for *Betula* and a clearer pattern of pollen behavior consisting of only one well-defined peak. Furthermore, it is worth mentioning, that intensity of the Poaceae pollen season was decreasing across examined years with 2019 having the lowest pollen abundance. Also, 2019 was the driest year, especially in the pollen season of Poaceae, both in terms of precipitation and relative humidity, which contributed to it being also the longest pollen season. Consequently, both applied machine learning techniques were constantly overestimating observed airborne pollen counts, especially in the weakly abundant beginning of the pollen season. An additional inclusion of a parameter reflecting expected intensity of the pollen season might have an essential effect on the accuracy of the predictive models. However, more historical pollen data are needed to investigate intensity of the Poaceae seasons.

Overall, a good predicting performance of simple seasonal ARIMA model in comparison to advanced forecasting techniques suggests that the phenology of the plants, reflected by the lagged pollen concentrations, is the most relevant predictor for the observed airborne pollen concentration. This insight is also supported by diurnal pollen concentration patterns discovered in the present study, especially for Poaceae, showing significant differences in airborne pollen concentrations depending on the time period of the measurement. This finding highlights the importance of the further, scrupulous investigation of the diurnal variation of the airborne pollen concentration and its influencing factors. Investigation of airborne pollen concentrations on hourly scales represents a promising research direction, since it accommodates one of the most urgent/important objective of the pollen, namely delivery of pollen information to people suffering from pollen-induced allergies. Given that under ongoing climate change conditions, increasing and more intense extreme weather events influence the abundance and seasonality and circadian periodicity of airborne pollen, developing accurate short-term forecasts is a real challenge. In our results, this is highlighted by the fact that the significantly drier year 2019 led to reduced predictive capacity of most models and signified past pollen records as the most reliable, in this dataset, predictor of future, on an hourly scale, pollen concentrations. It is anticipated that unexpected and extreme weather incidents may be already causing unpredictable pollen seasons and diurnal distribution, which is worth to be investigated more thoroughly.

When developing a forecasting model to notify the pollen allergic individuals about expected airborne pollen levels in order to support them in pollen allergy management, one has to keep in mind the needs of the target population. Allergic individuals might be hardly interested in pollen forecasting expressed in absolute values. On contrary, they might be interested in notifications of critical pollen values, or expected symptom severity induced by the airborne pollen levels. Firstly, this consideration can also affect the definition of the main pollen, taking into account pollen thresholds inducing allergic reaction of different severity in sensitized individuals (Karatzas et al. 2019, 2019). Secondly, there are several studies focusing on prediction of certain levels of airborne pollen concentration (Brighetti et al. 2014; Castellano-Méndez et al. 2005) or even expected season severity (Sánchez Mesa, Galán and Hervás 2005). Pollen level inducing an allergic reaction of a certain severity in allergic individuals might be variable for different locations due to different climatic conditions (Weger et al. 2013). The forecasting of critical values might be very useful for allergic individuals. However, so far, it lacks scientific efforts in this direction in Germany, and, thus, it lacks knowledge of pollen thresholds triggering allergic symptoms in sensitive individuals.

An important limiting factor of the present study is the volume of the available pollen data. As BAA500 has been operating in Augsburg for only half a decade, only four complete pollen seasons were available for the data analysis. Environmental data are known to be very complex to model due to underlying interrelations (Zewdie et al. 2019), thus, the data available for present research might be too little to determine the seasonal phenology of examined species or to identify and characterize anomalous pollen seasons. In order to realize and to calibrate forecasting models, long historical series of pollen and meteorological data are necessary. Furthermore, it is worth pointing out, that the predictive models presented in this study are based on data provided by an innovative fully-automated pollen monitor, which, being a novel device, is still undergoing improvements. Although the pollen monitoring already shows a high accuracy of pollen determination accounting for more than 90% (Oteros et al. 2015), a further improvement in recognition algorithm and consequently in accuracy of pollen recognition is possible and expected in near future (Schiele et al. 2019). The key for reliable, short-term pollen predictions does not necessarily lie on the complexity and how sophisticated the applied statistical techniques are, but on the completeness of the toolkit used toward this purpose:

- good quality of data (reliability)
- long datasets (consistency)
- considerations of the whole multi-factorial design
    - pollen autocorrelations
    - interaction effects with weather and climatic parameters
    - trends and periodicities.

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