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Learning activities in technology-enhanced learning: A systematic review of meta-analyses and second-order meta-analysis in higher education

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ABSTRACT

Models such as ICAP hypothesize that effects of technology-enhanced learning (TEL) are mediated by the learning activity that is facilitated by technology. In this systematic review of meta-analyses and second-order meta-analysis, we examined effects of instruction with versus without digital technology in higher education while considering students' learning activities in the technology and nontechnology conditions. Based on $N_{\mathrm{ES}} = 45$ eligible effects from $N_{\mathrm{MA}} = 28$ meta-analyses (that include $N_{\mathrm{primary}} = 1286$ effect sizes from primary studies), our results showed that when digital technology instruction was used as a substitute for nontechnology instruction, there was no substantial change in students' cognitive learning outcomes. However, cognitive learning outcomes improved when the technology provided learning-activity-specific support. Further, digital technologies that offered more advanced learning activities resulted in higher cognitive learning outcomes for students. Our results indicate that effects of TEL are mediated by the learning activity that is facilitated by technology.

Educational relevance and implications statement: Our study highlights the relevance of *how* digital technology is used during learning in higher education. Specifically, our study supports two proposed mechanisms of effective TEL, (a) enhancing the ICAP-level of learning activities and (b) facilitating specific learning activities and underlying cognitive processes through cognitive support. Thus, consideration of students' individual differences in learning activities when learning with digital technologies are crucial and can influence effects in empirical studies as well as meta-analyses. For practice, our results imply that promoting the engagement of all learners in active forms of learning (particularly constructive and interactive learning activities) with the help of digital technologies can foster students' learning in higher education. Additionally, digital technologies incorporating cognitive support (e.g., scaffolding, feedback, sequencing) for specific learning activities and its underlying cognitive processes can foster students' learning.

1. Introduction

Technology-enhanced learning (TEL) has been studied for decades (Tamim et al., 2011). During this time, thousands of experimental studies have been conducted and summarized in meta-analyses (e.g., Bernard et al., 2004). However, these meta-analyses have often focused on effects of specific digital technologies and their technology-specific features on learning outcomes. Therefore, a general analysis targeting the impact of digital technology on learning across different technologies is apparently difficult. Tamim et al. (2011) attempted to address this problem by combining multiple meta-analyses into a second-order meta-analysis but without providing empirical answers to the question of *why* digital technologies might have an impact on learning outcomes. They included 25 meta-analyses that compared instruction with and without digital technologies and found a significant but small overall weighted mean effect size (ES) for the effect of digital technology on students' learning outcomes with high heterogeneity in the results. According to Clark (1994)'s media debate, this heterogeneity is caused by differences in instructional methods rather than differences in technological features. These changes in instructional methods are often inherent to the respective digital technologies and might thus confound the effect of technology. Therefore, which kind of digital technology is employed may be less relevant. Rather, the important question may be how the technology is used in a learning context (Fütterer et al., 2022; Sailer

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et al., 2021; Wekerle et al., 2020).

One way to assess the use of digital technology in learning is to use the ICAP (*Interactive Constructive Active Passive*) model (Chi & Wylie, 2014) to classify the learning activities afforded to the students by the technology (see Stegmann, 2020). The ICAP model operationalizes students' learning activities (i.e., as interactive, constructive, active, and passive), which are approximations of different cognitive processes and different degrees of cognitive engagement (Chi, 2009; Chi & Wylie, 2014). It allows findings to be generalized from the digital technology implementations under investigation, and then the findings can be used to develop general recommendations for the use of digital technologies in TEL. This process seems especially necessary due to the progressive nature of digital technologies and their increasing implementation in higher education (Hamilton et al., 2016). The lack of sound recommendations has received broader attention as a result of the COVID-19 pandemic (Seufert et al., 2021), further highlighting the need for research that can inform teaching practices. Therefore, in this study, we conducted a systematic review of meta-analyses and second-order meta-analysis on the impact of digital technology instruction in higher education by using the ICAP classification to focus on student learning activities.

1.1. The role of changes in learning activities through technology-enhanced learning

Among others, research on TEL was synthesized by Hattie (2009). He distinguished between different categories of digital technology use, namely, interactive video methods, audiovisual methods, simulations, programmed instruction, and web-based learning. Although this distinction seems plausible from a technology-development perspective, it lacks an educational/psychological theory-driven approach for synthesizing the effects of TEL. For example, Mayer (2012) applied a more theory-driven approach to investigate effects of TEL. Based on a cognitive psychology perspective, the cognitive theory of multimedia learning adopts a systematic approach that formulates clear recommendations for TEL. However, research and recommendations based on the cognitive theory of multimedia learning clearly focus on the reception of content via digital technologies, but they tend to ignore other, more constructive learning activities that learners might engage in when interacting with digital technologies. However, focusing only on effects of TEL on students' reception of learning content might not allow more general recommendations to be made for TEL in more active, productive, and constructive learning scenarios, especially because, according to Tamim et al. (2011), digital technologies have the greatest potential for promoting various forms of active learning.

The application of a systematic approach for differentiating digital technology use by the learning activities it affords seems promising for deriving more general recommendations for the implementation of TEL. The ICAP model allows for such a systematic classification of different affordances provided by digital technologies by focusing on students' learning activities (Chi, 2009; Chi & Wylie, 2014). The notion of the ICAP model fits well with TEL research because, when the model is applied to TEL, the focus is on *how* students use technology and how they are most likely cognitively stimulated by it and engaged with it, instead of focusing on the frequency and types of technologies applied (Lachner et al., 2024; Reinhold et al., 2024; Sailer et al., 2021; Wekerle et al., 2020). As the acronym ICAP refers to interactive, constructive, active, and passive learning activities, the model operationalizes different types of observable learning activities as approximations of cognitive engagement in learning contexts. Cognitive engagement broadly refers to cognitive investment in learning (Chi et al., 2018), emphasizing the metacognitive effort involved (Greene, 2015). The learning activities that approximate cognitive engagement and are postulated by the ICAP model are based on four underlying cognitive processes with different knowledge-altering potential: *storing*, *activating*, *linking*, and *inferring*. On the basis of assumptions about probability, Chi (2009) postulated that different learning activities make certain cognitive processes more likely to happen.

Passive learning activities take place when attention is focused solely on listening, watching, or reading the given learning material, without any physical interaction. Therefore, learners' storing of new information is likely to occur in isolation, and the stored knowledge is likely to be applied only in identical contexts (Chi & Wylie, 2014). *Active* learning activities refer to students' physical engagement with and manipulation of given learning material and are also referred to as *hands-on learning activities*. By selecting or focusing on parts of the given learning material, learners are more likely to *activate* their prior knowledge and *link* the new information to the prior information before *storing* the new information (Chi, 2009). Examples of active learning activities include highlighting, copying and pasting, pausing/rewinding/fast-forwarding audio or video material, and answering questions that essentially require mere repetition of the given learning material (see Sailer et al., 2021). Passive and active learning activities can be allocated to the category of *shallow processing strategies* (Chi et al., 2018), which are characterized as rote processing strategies (Greene, 2015).

In contrast to shallow processing strategies, *deep processing strategies* involve elaboration of the material that is being learned (Craik & Lockhart, 1972). Constructive and interactive learning activities are classified at the levels of deep processing strategies (Chi et al., 2018). *Constructive* learning activities refer to students' generation of knowledge and ideas that go beyond the given learning material by independently comparing, explaining, questioning, arguing, and summarizing (Chi et al., 2018). In addition, applying knowledge and learning material to other contexts and solving problems (i.e., in serious games or simulations) are also considered generative and thus *constructive* (Brod, 2020). Due to their generative quality, *constructive* learning activities are connected by *inferring* new knowledge from prior knowledge that has been activated and *storing* the *inferred* knowledge. The last group of learning activities is composed of *interactive* learning activities. For this type of social learning activity to be present, students must meet the following requirements: Two or more individuals must interact reciprocally in a co-generative manner, and the activities the learners engage in must be constructive in the first place. Examples include collaborative problem solving, discussion, and argumentation (Chi et al., 2018). These interactive learning activities are likely to involve the cognitive processes *storing, activating, linking, and inferring*. In addition, processes of *co-inferring* are possible as learners are able to make inferences on the basis of their own knowledge and the knowledge of others (Chi & Wylie, 2014).

Given the assumed increase in the variety and quality of cognitive processes from *passive* to *interactive,* the ICAP model assumes a hierarchy and hypothesizes that the potential of enhancing learning increases along that continuum (Chi & Wylie, 2014). The classification of about 40 existing experimental studies into the ICAP framework and their comparison with regard to learning outcomes showed that interactive learning activities are superior to constructive ones, which are superior to active ones, which in turn are superior to passive learning activities (Chi, 2009; Chi & Wylie, 2014). No differences were found between studies on the same learning activity level. An experimental study with students learning in different ways according to the ICAP model also found results that were in line with the ICAP hypothesis (Menekse et al., 2013). However, when the measurement of the learning outcome was based only on the given information in the learning material, *interactive* learning activities did not result in better scores than *constructive* learning activities (Menekse et al., 2013).

In taking the ICAP theory and applying it to TEL research, we expect that digital technologies that are implemented in such a way that they either (a) facilitate specific learning activities at a certain level or (b) even enhance the ICAP level of students' learning activities will result in positive effects of the implementation of the digital technologies. Fig. 1 illustrates these two proposed mechanisms of TEL.

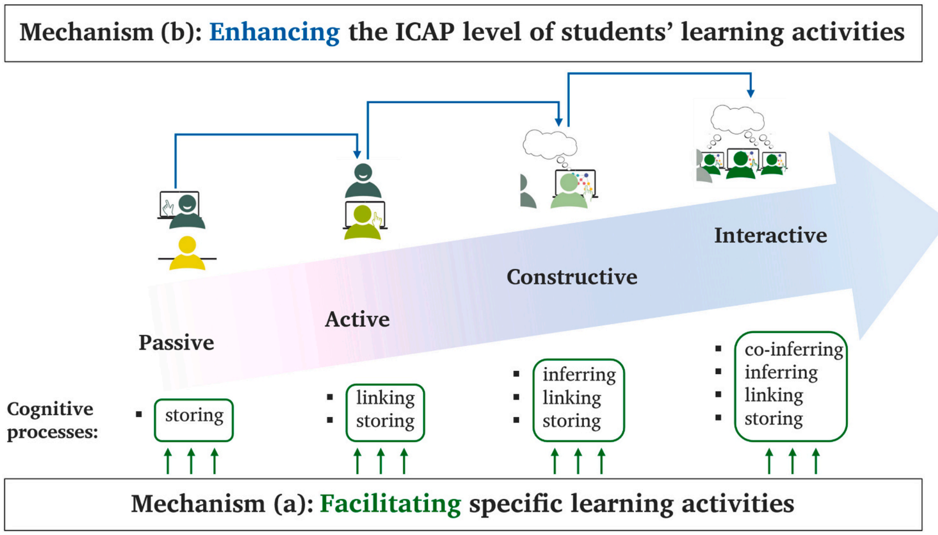

Fig. 1. Mechanisms of TEL to foster learning based on the ICAP Model: (a) facilitation of specific learning activities and (b) Enhancement of the ICAP Level of students' learning activities.

1.1.1. *Facilitation of specific learning activities*

Digital technologies have merit in that they can offer additional cognitive support for the learning processing that underlie a certain learning activity without changing it. They can offer support and feedback and thus optimize cognitive processes within a certain learning activity. Diverse learning theories focus on guiding instructors to provide the kind of support that is needed for specific learning materials, learning goals, and learners' learning prerequisites, such as cognitive load theory (Sweller et al., 2019), the script theory of guidance (Fischer et al., 2013), behavioral theories (Kirsch et al., 2004), constructivist theories (Tobias & Duffy, 2009), and sociocognitive theories (Glaser & Chi, 1988; Lave & Wenger, 1991; Piaget, 1965; Vygotsky, 1980). Instruction with digital technologies can increase the variety of functional enhancements and the possibility of providing the appropriate cognitive support and thereby positively influence students' cognitive processes and learning outcomes (Salomon & Perkins, 2005), for example, by offering adaptive support (Plass & Pawar, 2020).

In the ICAP model, this means that even though instruction with and without digital technologies might share an ICAP level, it can still vary in the extent and appropriateness of the cognitive support that is offered and, therefore, the potential to increase the likelihood or the quality of the underlying cognitive processes: *storing, activating, linking*, and *(co-) inferring*. In line with this argumentation, Wekerle et al. (2020) found that active learning activities with digital technology significantly predicted learning outcomes in higher education students, whereas non-digital active learning activities did not.

1.1.2. *Enhancement of the ICAP level of Students' learning activities*

One of the central mechanisms of TEL might be that it can increase the depth of cognitive processing and thus promote learning. This potential is particularly true for deep understanding, knowledge application, and problem solving (Chi et al., 2018; Sailer et al., 2021). This idea is in line with meta-studies that have emphasized that digital technologies have the highest potential to afford higher level learning activities (Tamim et al., 2011). For example, research on instruction in higher education has shown that students are more likely to engage in constructive learning activities when teachers use digital technology compared with nondigital instruction (Wekerle et al., 2020).

1.2. *ICAP-inspired SAMR model: Comparing effects of TEL from a learning activity perspective*

A model for systematically classifying implementations of digital technology is the SAMR model (Puentedura, 2006, 2014). SAMR differentiates on the basis of the extent to which the learning task is changed by the integration of digital technologies. Accordingly, the model categorizes comparisons between digital technology implementations and nontechnology implementations in the categories *substitution, augmentation, modification,* and *redefinition* (SAMR). If technology-free teaching methods are replaced by technology-supported methods, and the use of technology does not result in a functional change in the task, the technology is considered a *substitution*. If the learning task remains identical but the use of digital technology results in a functional improvement in the task, it is considered an *augmentation*. If technology integration leads to a significant redesigning of a task, it is referred to as a *modification*. Finally, if digital technology is used to create novel tasks, it is referred to as a *redefinition* (Puentedura, 2006, 2014). Puentedura (2014) hypothesized that as the degree of functional change increases from substitution to redefinition, so does the potential to enhance learning.

At first glance, the operationalization of the model might be plausible and, thus, the model has often been adopted in teaching practice (Hamilton et al., 2016). The SAMR model offers a practical framework for analyzing whether teachers and their specific implementations of technology truly capitalize on the potential of digital technology to enhance learning (Lachner et al., 2024). However, the model has been criticized for its lack of systematic empirical support, its rigid structure, and its focus on products instead of learning processes (Hamilton et al., 2016). From our perspective, the justified criticism of the SAMR model might be addressed by applying a learning activity perspective through the lens of the ICAP model.

Against this background, we propose an ICAP-inspired SAMR model. By doing so, the lack of process-orientation of the SAMR model (see Lachner et al., 2024) will be addressed while keeping its analytical focus on the comparison of implementations of TEL: For *substitutions* and *augmentations*, the students' learning activities are not changed by the use of technology. Thus, comparisons between instruction with and without technology operate on the same ICAP level. In addition, comparisons labeled *substitutions* refer to situations in which none of the students in different experimental conditions are offered additional support for their cognitive processes. In contrast to *substitutions*, *augmentations* offer an enhancement by providing additional support for cognitive learning processes through digital technology without changing the learning activity. *Modifications* lead to the redesigning of a task by changing the central learning activity through the use of digital technology. This change occurs within the level of shallow learning processes (a change between passive and active learning activities) or within deep learning processes (a change between constructive and interactive learning activities). Thus, learning activities are modified but are not changed in a significant way (i.e., because they don't change from shallow to deep learning processes; see Chi et al., 2018). When the change in the central learning activity occurs between shallow learning processes and deep learning processes, a *redefinition* is present. Fig. 2 illustrates the allocation of comparisons.

Based on this ICAP perspective, which we are applying to the SAMR framework here, effects of digital technology use can be allocated and discussed regarding their effectiveness for TEL in higher education.

1.3. The present study

In this study, we conducted a systematic review and second-order meta-analysis of individual ESs from meta-analyses in which instruction with digital technology was compared with instruction without digital technology in higher education. Thus, in our qualitative (systematic review) and quantitative analyses (second-order meta-analysis), we focused on effects from meta-analyses that were based on (quasi-) experimental designs. Furthermore, we used the ICAP model to allocate the students' learning activities from the technology and nontechnology experimental conditions. In addition, we classified the comparisons between the two conditions on the basis of our ICAP-inspired SAMR model.

On the basis of the theoretical considerations and empirical findings, we hypothesized that teaching with digital technologies would have a positive impact on higher education students' learning outcomes if it increased students' cognitive engagement with the learning material. This positive impact can be achieved, (a) on the one hand, by providing appropriate cognitive support for the successful execution of the cognitive processes *storing, activating, linking, inferring, or combinations*; or (b) on the other hand, by providing opportunities for higher learning activity levels with an increased likelihood of a broad variety of cognitive processes (*activating, linking, inferring, or combinations*).

Assuming that these two mechanisms occur in TEL resulted in the following three research questions:

RQ1. To what extent does digital technology impact learning outcomes in higher education when the use of digital technology does not change students' central learning activities?

We expect that, comparing groups in the two conditions (i.e., with and without digital technology) on the same ICAP level, would result in a positive effect for the TEL group only if the digital instruction provided adequate cognitive support for the successful execution of the cognitive processes *storing, activating, linking, inferring, or combinations*. Thus, we expect that only augmentations with cognitive support, and not implementations that served as substitutions, would lead to higher learning outcomes for TEL.

RQ2. To what extent does digital technology impact learning outcomes in higher education when the use of digital technology changes the students' central learning activities?

We assume that digital technologies that help students engage in higher learning activities will result in higher learning gains. If a change in the learning activity level were to occur, that is, if it changed from shallow cognitive processing to deep cognitive processing (i.e., redefinition), we would expect a higher learning gain compared with a change in learning activity levels within shallow or deep cognitive processing (i. e., modification).

RQ3. To what extent does the level of the ICAP-inspired SAMR model moderate the effect of digital technology on learning outcomes in higher education?

We expect that the level in our ICAP-inspired SAMR model moderates the effects of TEL in higher education. Based on the ICAP model, redefinitions lead to the highest ES, followed by modifications, followed by substitutions (see mechanisms b). Further, substitutions should not affect learning at all. While the ICAP model implies that an increase of effects of digital technology on learning requires an increase of ICAP-level, our ICAP-inspired SAMR model suggests that augmentations with cognitive support are supposed to foster learning as well (see mechanism a).

By addressing these research questions, we aim to derive to sound recommendations for the use of digital technologies in higher education for research and practice across boundaries of specific instructional approaches and/or digital technologies.

2. Method

We conducted a systematic review of meta-analyses and second-order meta-analysis to address the research questions. The procedure was inspired by the approach used by Stegmann (2020) to conduct a systematic review of TEL in the context of K-12 education. Hereby, we identified ESs from meta-analyses. These results gave us insights into the effects of instruction with digital technology compared with instruction without digital technology on learning outcomes in higher education. We classified the ESs into the ICAP model and the ICAP-inspired SAMR model.

2.1. Literature search

First, we identified existing meta-analyses that had been published by the end of 2011 by screening the reference lists of two second-order meta-analyses, which, among other factors, investigated TEL: Hattie (2009) and Tamim et al. (2011). For publications from 2012 or later, we conducted three advanced database searches: one on April 22, 2015, the second on March 18, 2021, and the third on November 23, 2023. The search terms and databases we used are provided in Supplement A. The literature search resulted in 5826 hits (see Fig. 3). All hits from all sources were screened for eligible ESs according to the following inclusion criteria.

2.2. Inclusion criteria

ESs from meta-analyses had to meet the following criteria to be included in this review. Judgments about eligibility were based on the information provided in the meta-analyses. This information had to

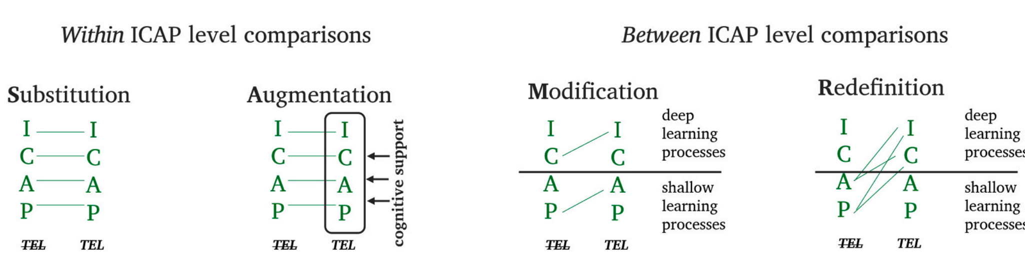

Fig. 2. ICAP-inspired SAMR model.

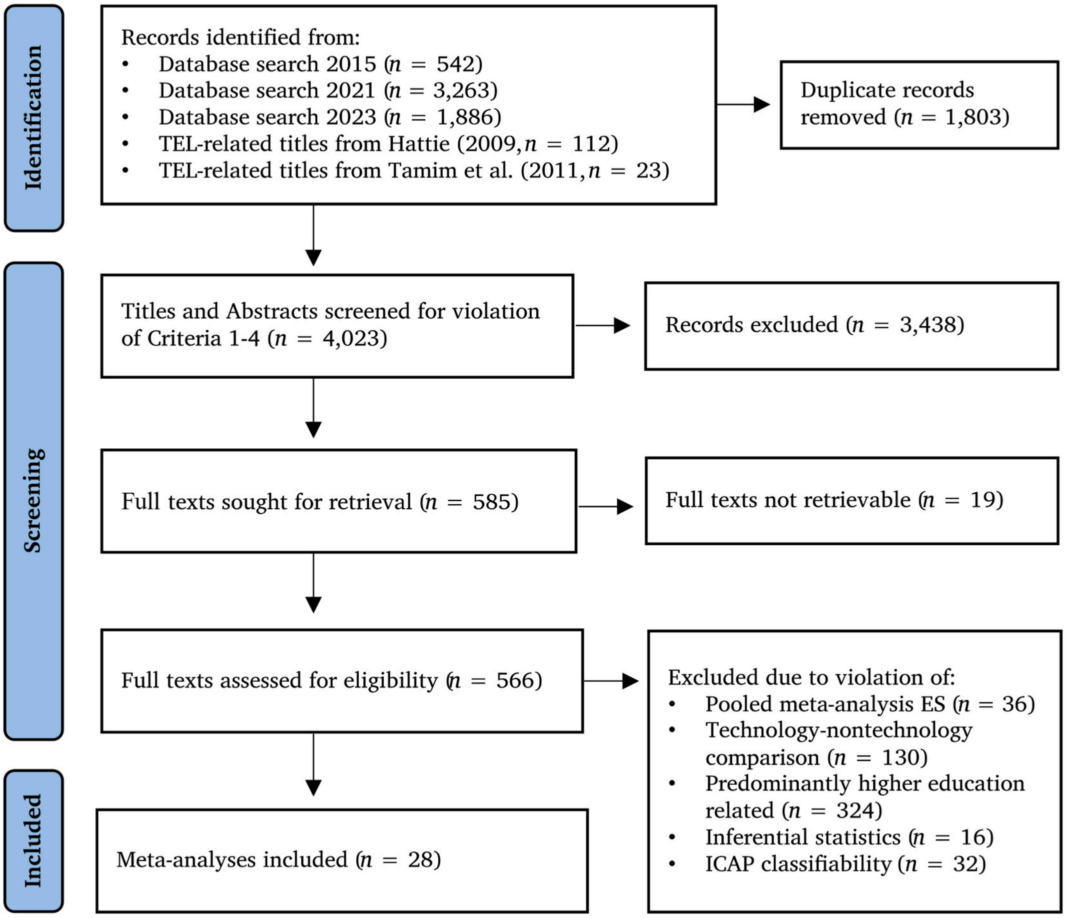

Fig. 3. Flow chart for meta-analyses included in the systematic review.

enable clear decisions about the following inclusion criteria:

1. Eligible ESs were published in meta-analyses written in English.
2. Eligible ESs were pooled on at least two quantitative primary studies.
3. Eligible ESs referred to the comparison of a teaching condition that used digital technology versus a teaching condition that did not use digital technology in a between-subjects design (i.e., experimental or quasi-experimental design) with both conditions receiving some form of instruction. Designs with waitlist control groups were excluded. We defined digital technology as computer-based technologies that are used to present information or to enable students to interact with the content as well as each other (Stegmann, 2020).
4. Eligible ESs referred to an objective learning outcome such as achievement, academic performance, grades, exams, test scores, number of correct answers, knowledge, retention, and measures of behavior or skills. Effects that were based on students' self-assessments of learning outcomes were excluded.
5. Eligible ESs referred predominantly (>50 %) to higher education students or settings (in line with the inclusion criteria applied by Schneider & Preckel, 2017). According to the definition of the UNESCO General Conference (1993), higher education includes postsecondary learning environments provided by approved institutions, where, after completing their K-12 education, individuals can qualify to pursue an additional higher education learning opportunity or can become prepared to pursue a profession. Generally, we considered universities, colleges, and medical schools to be higher education settings, and therefore, we included university students, college students, undergraduate students, and graduate students. We also included precollege students and baccalaureates because they are postsecondary, and as such, they participate in higher education precourses at higher education institutions.
6. Eligible ESs constituted a standardized mean difference (e.g., Cohen's *d*, Hedges' *g*, Glass's delta) and were presented with inferential statistics (e.g., confidence interval or *p*-value).
7. Control as well as experimental condition of eligible ESs could be clearly assigned to one learning activity level in the ICAP framework.

As shown in Fig. 3, trained coders first screened the Titles and Abstracts of our 4023 hits (without duplicates) for violations of Inclusion Criteria 1 to 4. The training data set was randomly selected. Three rounds of trainings were performed. Between each round, disagreements were discussed until 100 % agreement was achieved. At the end of the coding training sessions, the two coders reached an interrater reliability of Cohen's $\kappa = 0.75$.

We retrieved full texts through the libraries of affiliated universities, online databases, professional social networking sites (e.g., ResearchGate), and by directly contacting authors of the publications. From the remaining 585 hits, we were able to retrieve 566 full texts. We investigated the full texts one after another to determine their eligibility. To determine whether an ES referred predominantly to higher education (Inclusion Criterion 5), we determined the proportion of students in higher education in the corresponding meta-analysis (see Schneider & Preckel, 2017). We thereby favored information on the number of study participants over the number of (primary) studies over the number of ESs. If this information was not provided in the meta-analysis, the primary studies were scanned by Title and Abstract for determination. For meta-analyses that focused solely on higher education, all ESs were considered for further processing. If the percentage of students in higher education in a meta-analysis ranged from 51 % to 99 %, only those ESs for which the majority could still be ensured to be from higher education were included in our review. In meta-analyses in which higher education students were represented in only <50 % of the studies, we screened the meta-analysis for a sub analysis containing 100 % higher education students and included those ESs in cases in which such ESs were reported (e.g., Ozdemir et al., 2018).

In summary, 76 meta-analyses reported at least one ES that passed Inclusion Criteria 1 to 5 (see Fig. 3). However, 16 of these meta-analyses lacked inferential statistical results (Inclusion Criterion 6). Thus, 60 meta-analyses were included in the coding process for eligibility regarding Inclusion Criterion 7.

2.3. Coding procedure

To prevent having a bias toward single meta-analyses, we aimed to include one ES per meta-analysis in our analyses. If a meta-analysis included multiple eligible ESs and these ESs reflected different ICAP comparisons, learning outcomes, or SAMR levels, we included all ESs that investigated these aspects in a differentiated manner. We used either the overall effect size from the meta-analysis or the eligible ESs from a sub analysis to ensure independence of ESs as much as possible. We describe the step-by-step process, including the coding of the different ESs, in the following subsections.

2.3.1. Learning activities in the experimental conditions

The classification of the learning activity levels for the experimental conditions was based on the ICAP framework (Chi, 2009). The framework distinguishes four levels of cognitive engagement in learning contexts on the basis of different types of observable learning activities. The differentiation is thereby based on learners' behavior and the products they generate (Chi & Wylie, 2014). Due to the approach that we used to conduct this systematic review of meta-analyses, it was not possible to consider individual learning activities. Further, instruction and student activities cannot be expected to perfectly concur in learning environments (Chi et al., 2018). However, given that different learning opportunities increase the probability of certain students' learning activities, it is possible to assume a strong connection between students' learning activities and the learning opportunities afforded through teachers' instruction (Sailer et al., 2021). Therefore, we view the coding of the described learning conditions with and without digital technology as able to provide a sufficient approximation of students' learning activity levels.

Whenever the learning conditions suggested that the students received content only in the forms of printed text (Steenbergen-Hu & Cooper, 2014), static pictures and animations (Höffler & Leutner, 2007), or lecture-based instruction (Tudor Car et al., 2019), we coded them as *passive*. For the integration of methods such as drill and practice (Viljoen et al., 2019) or audience-response systems (Hunsu et al., 2016), which require or result in active reactions to or manipulations of the learning material, we assigned the code *active*. We assigned the code *constructive* to learning activities that required students to add their own considerations that went beyond the learning material and to activities that were generative in nature (Brod, 2020). This is the case when students engage in problem-solving tasks during simulation-based learning (Ozdemir et al., 2018), when they write original text passages (Al-Wasy, 2020), or when they perform computations and calculations (Sosa et al., 2011). If co-construction of knowledge by two or more students was possible in collaborative situations, we coded the learning activity as *interactive* (Kyaw et al., 2019).

If different learning activity levels were subsumed under one learning condition, three scenarios were distinguished: First, when the activity level varied across the primary studies included in the pooled effect size, with at least 70 % sharing an activity level, the activity level of the majority of studies was coded. Second, when the activity level varied within the primary studies included in the pooled ES and therefore co-occurred in a real (classroom) learning scenario, the highest ICAP level was coded because, according to the ICAP model, higher learning activity levels subsume the lower learning activity levels (Chi & Wylie, 2014). Third, when neither was the case, the effect size was excluded from our systematic review.

As the students' learning activities in the conditions were not always described in detail in the meta-analyses—especially for the control condition—we used state-of-the-art knowledge about technical terms as well as learning and instruction to code the learning activities in the conditions: We considered standard institutional learning conditions (e.g., traditional, conventional, face-to-face, classroom instruction) to be *active* because they typically included phases of reception of knowledge combined with hands-on activities involving the learning material (Chi et al., 2018). Such a constellation can be described as a typical seminar situation in higher education. We also considered computer-assisted or computer-based instruction and web-based or distance education without further description to be standard instruction and therefore coded these as *active* as well. ICAP coding training was conducted in eight rounds by five coders, including 1267 ESs from 36 meta-analyses. The training data set was randomly selected from meta-analyses that passed Criteria 1 to 4. Between each round, disagreements were discussed until 100 % agreement was achieved. At the end of the coding training sessions, the five coders reached an interrater reliability of Cohen's $\kappa_{median} = 0.79$ ($\kappa_{min} = 0.59$, $\kappa_{max} = 0.89$).

In summary, of the 60 meta-analyses that met criteria 1–6, 28 meta-analyses were eligible based on the ICAP coding, encompassing 39 ESs.

2.3.2. Learning outcomes

To capture the types of learning outcomes associated with the respective ESs, we differentiated between conceptual knowledge and application-oriented knowledge. *Conceptual knowledge* describes the repetition of facts and decontextualized information. Application-oriented knowledge includes procedures that involve "knowing how, when and why" (Förtsch et al., 2018; Johannsen et al., 2019). Thus, we assigned the codes *conceptual knowledge*, *application-oriented knowledge*, or *mixed* when both types of outcomes were synthesized in an ES. Outcomes that were solely labeled learning outcomes, achievement, tests, or grades (e.g., Shi et al., 2020) were coded as *conceptual knowledge.* For an outcome to be considered *application-oriented knowledge*, testing had to include behavioral outcomes, production-related outcomes, or knowledge application (e.g., Chen et al., 2018). Two independent coders achieved perfect agreement.

In three of the 39 ESs we included, further differentiations regarding learning outcomes were eligible, resulting in the inclusion of 43 ESs for further processing.

2.3.3. Comparisons of instruction with and without technology

In a next step, we used the SAMR model to code the ESs from the comparisons of instruction with and without technology, and we complemented the SAMR model with the ICAP model. For this purpose, we additionally considered eligible ESs from sub analyses out of the 43 ESs included so far that potentially indicated different SAMR levels by addressing different (didactic) implementations of the instruction in the nontechnology or technology condition. This was potentially the case for four ESs, resulting in a total of 50 ESs that we coded. These were labeled *substitutions* or *augmentations* if the nontechnology and technology conditions shared the same ICAP level (27 ESs); *modification* if the technology condition's ICAP level was enhanced from *passive* to *active* or *constructive* to *interactive* (three ESs)*;* and *redefinition* if the learning activity level of the technology condition was *constructive* or *interactive* in comparison with a *passive* or *active* nontechnology condition (20 ESs).

Whether a comparison within the same ICAP level constituted an *augmentation* or a *substitution* depended on whether the technology-based instruction provided additional support for cognitive processes (storing, activating, linking, and inferring), for example, through scaffolding (e.g., Taj et al., 2016) or corrective feedback (e.g., Grgurović et al., 2013) or not. We coded comparisons with cognitive support from digital technologies as *augmentations* and comparisons without additional cognitive support as *substitutions*. Two independent coders were trained in two rounds. In the first round, seven out of 27 ESs, which shared the identical ICAP classification, were randomly chosen for coding. Disagreements were discussed until 100 % agreement was achieved. In the second round, five new randomly selected ESs were coded by the two independent coders. In this round, they reached perfect agreement.

If the additionally included ESs from the subanalyses regarding different (didactic) implementations resulted in different SAMR levels, we selected them and excluded the overall ES. Otherwise, we disregarded the subanalysis ESs and selected the overall ES. Eventually, 22 of the 27 ESs that potentially distinguished between substitution and augmentation were included.

In total, we included 45 ESs from 28 meta-analyses as the final data set for our study.

2.4. Extraction of meta-analytic features and effect sizes

We extracted the following information from the meta-analyses: type of higher education students and the relative proportions of all the participants that were included, descriptions of the instruction with and without technology, and context (topic or domain). In a next step, we

Table 1
Included meta-analyses with topic of study, publication year of primary studies, percentage of students in higher education, applied statistical model, investigation of publication bias, correction of outliers, and interrater reliability.

Reference	Topic	Primary studies' publication year	Percentage of higher education students	Statistical model	Publication bias	Correction of outliers	Interrater reliability
Akın (2022)*	Mathematics education	2000–2020	27 %†	REM	No indication of bias	Not reported	Reported
Al-Wasy (2020)	Foreign language learning	2012–2018	56 %†	REM	Not reported	Not reported	Not reported
Bernard et al. (2004)*	STEM and business education	1985–2002	88 %	Not reported	Not reported	Applied	Reported
Cao and Hsu (2023)	STEM education	2008–2021	61 %	REM	No indication of bias	Applied	Reported
Chen et al. (2018)	Mainly health education and other studies	2012–2016	100 %	REM	No indication of bias	Not reported	Reported
Dixon et al. (2021)	Language learning	2000–2021	100 %	REM	No indication of bias	Not reported	Reported
Grgurovic et al. (2013)*	Foreign language learning	1970–2006	76 %	Not reported	Not reported	Not reported	Reported
Gui et al. (2023)*	STEM education	2005–2020	28 %†	REM	No indication of bias	Applied	Reported
Höffler and Leutner (2007)*	Mainly STEM and other studies	1973–2003	65 %	REM	Indication of bias	Applied	Not reported
Hunsu et al. (2016)*	Mainly science and engineering	1998–2014	96 %	FEM	No indication of bias	Not reported	Reported
Kyaw et al. (2019)	Medical education	2000–2017	100 %	REM	Not reported	Not reported	Reported
Li (2023a)*	Foreign language learning	2000–2022	57 %	REM	No indication of bias	Applied	Not reported
Li (2023b)*	Foreign language learning	2000–2022	62 %	REM	No indication of bias	Applied	Not reported
Mahdi (2018)*	Foreign language learning	2001–2017	62–81 %	REM	Not reported	Not reported	Not reported
Mihaylova et al. (2022)*	Language learning	2007–2019	78 %	REM	No indication of bias	Applied	Reported
Mitchell and Ivimey-Cook (2023)	Medical education	2011–2021	32 %†	REM	No indication of bias	Not reported	Not reported
Mukawa (2006)*	Foreign language learning, computer science education, medical education, business education, and others	2001–2006	88 %	Not reported	Not reported	Not reported	Reported
Ozdemir et al. (2018)	Mainly natural sciences and social sciences	2007–2017	19 %†	REM	Not reported	Not reported	Reported
Seyyedrezaei et al. (2022)*	Language learning	1990–2020	78 %	REM	Indication of bias	Applied	Reported
Sharifi et al. (2018)*	Foreign language learning	1990–2016	72 %	REM	No indication of bias	No correction necessary	Reported
Shi et al. (2020)	STEM, medical education, social science education	2006–2019	100 %	REM	No indication of bias	No correction necessary	Reported
Sosa et al. (2011)*	Statistics education	1974–2005	87–98 %	MEM	No indication of bias	Applied	Reported
Steenbergen-Hu and Cooper (2014)*	Mainly STEM education and business education	1990–2011	100 %	REM	Indication of bias	Applied	Reported
Taj et al. (2016)	Foreign language learning	2008–2015	62 %	Not reported	Indication of bias	Not reported	Not Reported
Tudor Car et al. (2019)	Medical education	1997–2017	100 %	REM	Not reported	Not reported	Not Reported
Viljoen et al. (2019)	Medical education	1965–2017	95 %	REM	Not reported	Not reported	Reported
Zeng et al. (2023)	Medical education	2006–2019	57 %	FEM	No indication of bias	Not reported	Not reported
Zheng et al. (2023)*	Mainly social sciences and STEM	2012–2021	70 %	REM	No indication of bias	Not reported	Reported

Note. *meta-analyses included in the second-order meta-analysis. † For these meta-analyses, we included the higher education-specific ES. Thus, the percentage of higher education students was 100 %.

extracted the methodological features of the meta-analyses. The methodological rigor of the respective meta-analysis plays an important role because it influences the accuracy of the effect (Borenstein & Hedges, 2019). We therefore examined the data set containing the meta-analyses by considering the publication date and whether the authors considered publication bias, controlled for outliers, considered the design of primary studies, and reported sufficient interrater reliability. We further extracted how the ESs were synthesized, that is, whether the authors integrated them through a fixed-effect model or a random-effects model, and which significance tests the effects were tested on. The benefit of random-effects models (over fixed-effect models) is that they account for differences across participants and differences in how the interventions are implemented because they are based on the assumption that the true effect varies between primary studies. Moreover, random-effects models offer the opportunity to generalize findings to other instructional scenarios, whereas fixed-effect models are limited in this regard (Borenstein et al., 2009). In addition, we extracted the number of primary studies and/or the number of ESs from primary studies for each synthesized ES in our review and examined whether the included ESs were independent and homogeneous.

When given a choice between an ES synthesized through a fixed-effect model and a random-effects model, we preferred the latter.

In a final step, we extracted concrete ESs, the confidence interval or *p*-value, and information about how the standard mean difference was calculated: Hedges' *g* with a correction for small sample sizes, Cohen's *d* without a correction for small sample sizes, and SMD without any further description. The meta-analysis by Taj et al. (2016) reported Fischer's Z_r. To enhance comparability, we transformed Fischer's Z_r into Cohen's *d* (see Borenstein et al., 2009). The ESs were interpreted as small (> 0.20), medium (> 0.50), or large (> 0.80) according to the standards set forth by Cohen (1977).

3. Results

We conducted a systematic review of meta-analyses to answer RQ1 (see 3.1) and RQ2 (see 3.2). To answer RQ3, we conducted a second-order meta-analysis (see 3.3).

Overall, ESs from 28 meta-analyses were included in this systematic review (see Table 1). The meta-analyses were published between 2004 and 2023. They were based on 1286 ESs from primary studies from 1965 to 2021. 19 meta-analyses reported checks for potential publication bias (see Table 2). Four of those could not rule out publication bias. Twelve meta-analyses investigated the necessity for the correction of outliers. 21 meta-analyses used random-effects models (REM), two used a fixed-effects model (FEM), one used a mixed-effects model (MEM), and the rest (four meta-analyses) did not report which model they used for primary effect integration. 19 meta-analyses reported interrater reliability with respect to the coding process, and nine did not. The ESs were calculated using Hedges' *g*, Cohen's *d*, or Fischer's Z_r and tested for 95 % confidence intervals.

From the 28 meta-analyses, 45 ESs were eligible for our systematic review. ESs were clustered by comparisons within the same learning activity level (RQ1; see 3.1) and between different learning activity levels (RQ2; see 3.2). For our and second-order meta-analysis (RQ3; see 3.3), we included all meta-analyses from our systematic review that reported Hedges' *g*. Accordingly, 16 meta-analyses and 25 ESs were included in the second-order meta-analyses.

3.1. Effects of TEL without changing Students' learning activities

Overall, 22 ESs referred to comparisons of instruction with and without technology in higher education in which the two conditions had the same learning activity levels according to the ICAP model. The ESs varied from $g = -0.25$, 95 % CI [−0.72, 0.22] (Steenbergen-Hu & Cooper, 2014, ES1) to $d = 2.13$, 95 % CI [1.09, 3.00] (Al-Wasy, 2020), indicating a broad range of ESs for TEL when comparing instruction that occurred on the same ICAP level. Nine ESs referred to *substitutions* with digital technologies, 13 ESs referred to *augmentations* with additional cognitive support through digital technologies (see Table 2).

3.1.1. Substitutions with digital technologies

ESs that referred to comparisons between instruction with and without technology but did not provide additional cognitive support for cognitive processes through the technology and did not change the learning activity could be assigned to the *substitution* category. We assumed that substitutions would not result in a significant positive effect for TEL. ESs ranged from $g = -0.25$, 95 % CI [−0.72, 0.22] (Steenbergen-Hu & Cooper, 2014, ES1) to $SMD = 0.18$, 95 % CI [−0.20, 0.55] (Kyaw et al., 2019, ES1). All nine ESs were nonsignificant. Fig. 4 shows an overview of ESs that refer to substitutions.

For *active* learning activities, five ESs were categorized as substitutions. Viljoen et al. (2019, ES1) reported effects of substituting stand-alone computer-assisted instruction for traditional face-to-face instruction in the field of medical education. The two conditions implemented similar features, and none of the groups stood out regarding the support they offered for cognitive processes. The ES was not significant. Similarly, Bernard et al. (2004) compared face-to-face instruction with distance (synchronous and asynchronous) education. This comparison showed a nonsignificant effect. In the field of language learning, Dixon et al. (2021) also conducted a comparison between traditional face-to-face instruction and various forms of hybrid instruction (namely, blended, synchronous, and asynchronous online methods), finding the difference in effectiveness to be nonsignificant. In a similar direction, Mukawa (2006) compared face-to-face instruction with distance education and blended learning, resulting in a nonsignificant effect. Hunsu et al. (2016, ES1) compared question-driven conventional lectures with lectures that included clicker-based digital technologies. The result of the comparison was nonsignificant.

Comparisons of two conditions that both engaged in constructive learning activities were investigated in one meta-analysis: Steenbergen-Hu and Cooper (2014, ES1) investigated comparisons of human tutoring with an intelligent tutoring system and found a nonsignificant effect.

Interactive learning activities in both the technology and non-technology conditions were investigated in three meta-analyses, all from medical education. Tudor Car et al. (2019, ES1) synthesized comparisons of traditional problem-based learning in small groups and face-to-face problem-based learning in small groups in which the actual problem was introduced in a technology supported way. The comparison resulted in a nonsignificant effect. Similarly, comparisons of standard curriculum including small group discussions with blended video-based digital instruction, which incorporated similar features, showed two nonsignificant effects on knowledge, (Kyaw et al., 2019, ES1), and on communication skills (Kyaw et al., 2019, ES2).

For *passive* learning activities, we did not find any eligible ESs.

Digital technology implementations that were classified as substitutions showed nonsignificant results. Without the augmentation with cognitive support, TEL had no positive effect on learning.

3.1.2. Augmentations with cognitive support for learning activities

With regard to cognitive support for the cognitive processes of *storing*, *activating*, *linking*, or *inferring*, we assumed that TEL would lead to a positive effect only if augmentations with additional cognitive support were available compared with the nontechnology condition. 13 ESs implemented such cognitive support in their technology implementations and represent *augmentations* (see Table 2). The ESs from these comparisons varied from $g = 0.24$, 95 % CI [0.14, 0.33] (Grgurović et al., 2013) to $d = 2.13$, 95 % CI [1.09, 3.00] (Al-Wasy, 2020). All of the effects indicated significant positive results (see Fig. 5).

Our review shows a broad variety of cognitive support on all levels of learning activities (*passive*, *active*, *constructive*, and *interactive*):

Höffler and Leutner (2007)'s study is the only one to report comparisons of *passive* learning activities in the two conditions. They

Table 2

Effects of comparisons within the same learning activity level with descriptions of both technology and nontechnology conditions, assignment to ICAP-inspired SAMR model and ICAP model, measured learning outcome, effect size, and 95 % confidence interval, number of primary effect sizes as well as primary studies included with that effect, and investigations of the homogeneity of the effect.

ES reference	Nontechnology condition	Technology condition	SAMR	ICAP	Learning outcome	ES	95 % CI	Primary ESs (studies)	Homogeneity of the effect
Bernard et al. (2004)	Face-to-face classroom instruction	Distance education (synchronous and asynchronous)	S	A vs. A	Mixed	$g = 0.01$	[−0.01, 0.03]	318 (>232)	No
Dixon et al. (2021)	Traditional face-to-face instruction	Hybrid language instruction (blended, synchronous online, and asynchronous online instruction)	S	A vs. A	Application-oriented knowledge	d = 0.14	[−0.10, 0.43]	24 (9)	Not reported
Hunsu et al. (2016), ES1	Question-driven conventional lectures	Clicker-based technologies with multiple-choice questioning	S	A vs. A	Mixed	$g = 0.00$	[−0.04, 0.03]	45 (45)	No
Mukawa (2006)	Face-to-face instruction	Online distance education and blended learning	S	A vs. A	Conceptual knowledge	$g = 0.14$	[−0.06, 0.33]	25 (25)	Yes
Viljoen et al. (2019), ES1	Traditional face-to-face instruction for electrocardiogram teaching (including lecturer/tutor interactions)	Computer-assisted instruction	S	A vs. A	Application-oriented knowledge	$d = 0.03$	[−0.49, 0.19]	5 (5)	Not reported
Steenbergen-Hu and Cooper (2014), ES1	Human tutoring	Intelligent tutoring system	S	C vs. C	Conceptual knowledge	$g = -0.25$	[−0.72, 0.22]	3 (3)	Yes
Kyaw et al. (2019), ES1	Traditional learning including small group discussions and role play	Blended video-based digital education, including team discussion and role play	S	I vs. I	Conceptual knowledge	$SMD = 0.18$	[−0.20, 0.55]	2 (2)	No
Kyaw et al. (2019), ES2	Traditional learning including small group discussions and role play	Blended video-based digital education, including team discussions and role playing	S	I vs. I	Application-oriented knowledge	$SMD = 0.15$	[−0.26, 0.56]	4 (4)	No
Tudor Car et al. (2019), ES1	Text- or paper-based problem-based learning in small collaborative groups	Face-to-face problem-based learning with the presentation of digital problems in small collaborative groups	S	I vs. I	Mixed	$SMD = 0.04$	[−0.20, 0.28]	4 (4)	Yes
Höffler and Leutner (2007)	Learning with static pictures	Learning with computer-based instructional animations	A	P vs. P	Mixed	$g = 0.37$	[0.25, 0.49]	76 (26)	No
Grgurović et al. (2013)	Traditional classroom instruction	Computer-assisted language learning	A	A vs. A	Mixed	$g = 0.24$	[0.14, 0.33]	49 (37)	Not reported
Li (2023a)	Traditional methods for vocabulary learning	computer-mediated feedback for vocabulary learning	A	A vs A	Conceptual knowledge	$g = 0.85$	[0.65, 1.06]	28 (25)	No
Mahdi (2018)	Traditional language learning	Mobile-assisted language learning	A	A vs. A	Conceptual knowledge	$g = 0.67$	[0.46, 0.72]	16 (16)	No
Mihaylova et al. (2022)	Traditional methods in language learning	Mobile-assisted language learning	A	A vs. A	Mixed	$g = 0.88$	[0.62; 1.14]	19 (19)	No
Sharifi et al. (2018)	Face-to-face language learning classroom instruction	Computer-assisted language learning and web-based learning	A	A vs. A	Mixed	$g = 0.50$	[0.43, 0.60]	158 (140)	No
Taj et al. (2016)	Traditional language learning	Mobile-assisted language learning	A	A vs. A	Conceptual knowledge	$d = 0.89$*	[0.32, 0.53]	13 (13)	Not reported
Viljoen et al. (2019), ES2	Traditional face-to-face instruction for electrocardiogram teaching (including lecturer/tutor interaction)	Blended learning, computer-assisted instruction	A	A vs. A	Application-oriented knowledge	$d = 0.84$	[0.54, 1.14]	3 (3)	Not reported
Al-Wasy (2020)	Traditional ways of teaching language writing	Technology-based language writing teaching	A	C vs. C	Application-oriented knowledge	$d = 2.13$	[1.09, 3.00]	10 (10)	No
Li (2023b)	Traditional methods in writing	Automated writing evaluation tools	A	C vs. C	Application-oriented knowledge	$g = 0.43$	[0.27, 0.59]	33 (25)	No
Seyyedrezaei et al. (2022), ES1	Non-technology writing instruction	educational technology in writing class	A	C vs. C	Application-oriented knowledge	$g = 0.80$	[0.53, 1.07]	30 (30)	No
Steenbergen-Hu and Cooper (2014), ES2	Self-reliant learning (including laboratory exercise without support)	Intelligent tutoring system	A	C vs. C	Conceptual knowledge	$g = 0.82$	[0.44, 1.20]	5 (5)	Yes
Tudor Car et al. (2019), ES2	Text- or paper-based problem-based learning in small collaborative groups	Distance-based digital problem-based learning in small collaborative groups with support for collaboration	A	I vs. I	Mixed	$SMD = 0.57$	[0.23, 0.92]	2(2)	Yes

Note. *ESs transformed from Fischer's Z_r to Cohen's d.

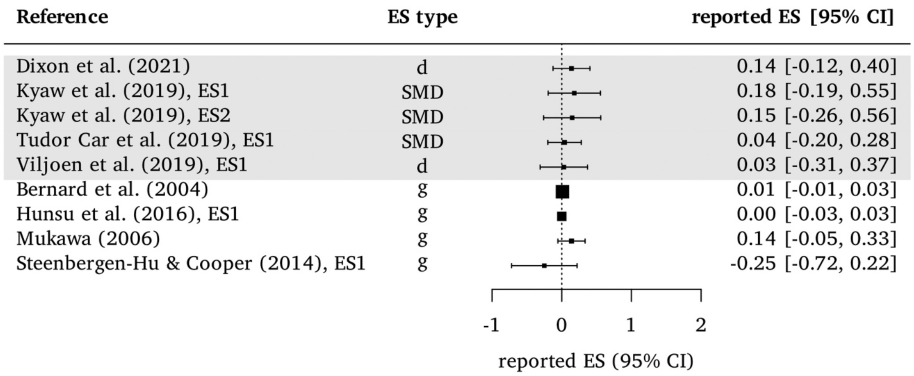

Fig. 4. Forest plot with reported effect sizes (ES) of substitutions with digital technologies differentiated by ES type (SMD: standardized mean difference; d: Cohen's d; Hedges' g). The point estimate of the meta-analysis result is represented by a black box. Horizontal lines representing the 95 % confidence intervals, with each end of the line representing the boundaries of the confidence interval.

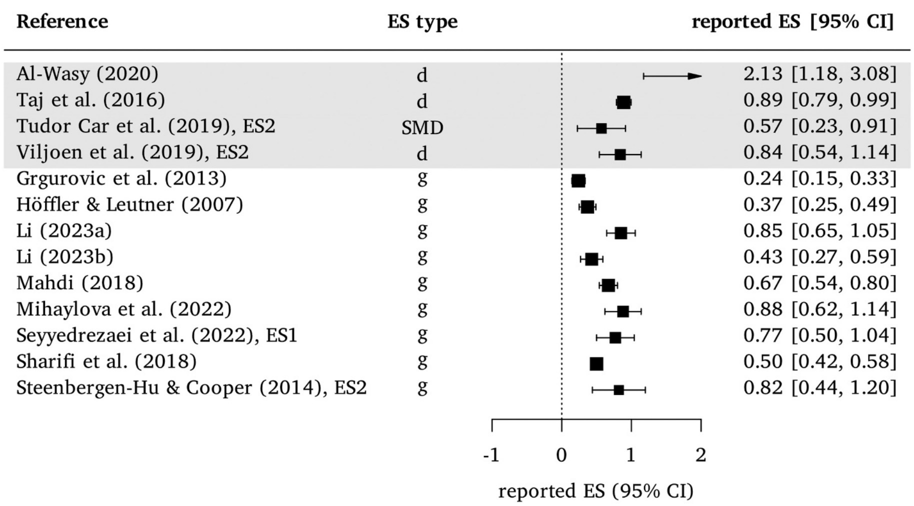

Fig. 5. Forest plot with reported effect sizes (ES) of augmentations through digital technologies differentiated by ES type (SMD: standardized mean difference; d: Cohen's d; Hedges' g). The point estimate of the meta-analysis result is represented by a black box. Horizontal lines representing the 95 % confidence intervals, with each end of the line representing the boundaries of the confidence interval (in case of extreme values, arrows show that boundaries are located outside of the limits of the visualized range of values).

examined the use of computer and video-based instructional animations compared with static pictures primarily in science education and found that the animations had a significant, positive small effect. Instructional animations provided the opportunity to illustrate the flow of the process and allowed for sequencing (see Sweller et al., 2019), thus providing cognitive support for the cognitive process of *storing*.

Regarding *active* learning activities, seven ESs represented results in which learners were provided with augmented cognitive support through the use of digital technologies. Viljoen et al. (2019, ES2) found a large positive effect when comparing traditional face-to-face instruction with computer-assisted instruction in medical education. Similarly, Sharifi et al. (2018) compared face-to-face instruction with computer-assisted instruction for learners and found a significant, positive, and medium-sized effect. Fife ESs stemmed from meta-analyses conducted in the context of language learning: Grgurović et al. (2013) reported a synthesized effect from computer-assisted language learning that was positive and small. Taj et al. (2016) compared nondigital vocabulary learning with mobile-assisted language learning. The ES in favor of the technology condition was large and significant. Mahdi (2018) also synthesized effects of mobile-assisted language learning on vocabulary learning regarding conceptual knowledge. He found a significant medium-sized effect of technology instruction. Effects on mobile-assisted language learning on conceptual as well as application-oriented knowledge were synthesized by Mihaylova et al. (2022), who reported a large effect size compared to traditional language learning methods. In the context of vocabulary learning, Li (2023a) also observed a large effect of computer-mediated feedback over traditional methods. These seven positive effects from meta-analyses refer to comparisons in which the technology-based instruction was provided with additional cognitive support for *storing*, *activating*, and *linking* by implementing corrective and automated feedback, scaffolding (including fading; see Belland et al., 2017), and (linguistic) support.

Regarding *constructive* learning activities, three ESs referred to an augmentation that offered cognitive support from digital technologies. Al-Wasy (2020) reported a large effect for technology-based second-language learning compared with traditional second-language learning. Focusing on writing skills, the participants in the TEL condition were given scaffolds to support their document editing, indicating cognitive support for *storing*, *activating*, *linking*, or *inferring*. Similarly, Li (2023b) and Seyyedrezaei et al. (2022, ES1) compared automatic writing evaluation tools and educational technologies in writing class with non-technology writing instruction. Their findings indicated a small effect size in the case of Li (2023b), and a medium-sized effect size in the study by Seyyedrezaei et al. (2022, ES1) for TEL. In the context of medical education, Steenbergen-Hu and Cooper (2014, ES2) reported a positive effect when comparing self-reliant learning with intelligent tutoring systems that provided scaffolding to students.

The meta-analysis by Tudor Car et al. (2019, ES2) was the only study that compared interactive learning activities and the implementation of an augmentation with cognitive support. Synthesizing effects of studies on medical students who engaged in traditional problem solving compared with distance-based digital problem solving that was augmented with a scaffolded collaboration, the results showed a medium-sized effect.

All ESs that included augmentations showed significant positive results, indicating the potential of digital technologies to augment cognitive support to the different cognitive processes that occur when people engage in different learning activities.

3.2. Effects of TEL involving changes in Students' learning activities

Overall, 23 ESs referred to comparisons of instruction with and without technology in higher education in which the experimental conditions differed in their learning activity level. In all 23 eligible effects, the condition in which instruction included technology had a higher learning activity level as defined by the ICAP model. Two ESs examined a change in learning activity within shallow learning processes, that is, a leap from passive to active learning activities. One ES analyzed a transition within deep learning processes, specifically a shift from constructive to interactive learning activities. These three ESs could be assigned to the category of *modification*. 20 ESs synthesized comparisons in which a leap in learning activities from surface learning processes to deep learning processes took place (from passive/active to constructive/interactive). These effects belonged to the category of *redefinition* (see Table 3).

3.2.1. Modifying learning activities with digital technologies

ESs that referred to comparisons between instruction that involved versus did not involve technology with a change in learning activity level within shallow learning processes (passive and active) or within deep learning processes (constructive and interactive) could be assigned to the *modification* category. In total, we found three eligible ESs that indicated significant positive results (see Fig. 6).

Two of them with a comparison of passive learning activities (nontechnology condition) with active learning activities (technology condition): Sosa et al. (2011, ES1) compared lecture-based instruction with computer-based instructional tools and web-communication tools, which were primarily implemented as distance education. The topic of the study was statistics. In the technology condition, students used audience-response systems, resulting in a significant, small, and positive effect. In a similar direction, Hunsu et al. (2016, ES2) compared conventional lectures with lectures that included audience-response systems. Most of the synthesized primary studies referred to the topics of science and engineering. The effect was significant and very small.

One ES referred to a comparison of constructive learning activities (nontechnology condition) with interactive learning activities (technology condition) and thus a comparison within deep learning processes: Seyyedrezaei et al. (2022, ES2) compared non-technology writing instruction with the use of peer feedback via collaborative technologies in language learning. The effect in favor of the collaborative technology group was large.

Although only three ESs referring to modifications were eligible for our systematic review, the direction of the effect was an indicator that enhanced learning activity levels with digital technologies might have the potential to improve learning outcomes.

3.2.2. Redefining learning activities with digital technologies

Comparisons of instruction that involved versus did not involve technology with a significant change in learning activity level from shallow learning processes (passive and active) to deep learning processes (constructive and interactive) could be assigned to the category of *redefinition*. We found 20 ESs that referred to a significant change in learning activity level (see Fig. 7).

Six effects compared *passive* learning activities in the nontechnology condition with *constructive* learning activities in the technology condition: Steenbergen-Hu and Cooper (2014, ES3) synthesized comparisons of students reading texts with students learning with intelligent tutoring systems in contexts focusing on STEM education. The authors reported a significant medium-sized effect of TEL. In the context of learning statistics, Sosa et al. (2011, ES2) compared traditional lecture-based teaching with the use of number crunchers (e.g., statistical software) that allowed the students to analyze data themselves. This comparison resulted in a significant medium-sized effect in favor of TEL. Shi et al. (2020, ES1) compared traditional instruction with technology-enabled active learning environments that included problem solving and flipped classrooms (see Bredow et al., 2021). The resulting effect was significant and large. Chen et al. (2018) compared lecture-based instruction with flipped classroom approaches. ESs were reported regarding three learning outcomes: examination scores (Chen et al., 2018, ES1), course grades (Chen et al., 2018, ES2), and objective structured clinical examinations (Chen et al., 2018, ES3). Whereas the first two effects were positive, the third was nonsignificant but with large confidence intervals and based on only two studies.

Two effects were from comparisons of *passive* instruction without technology versus instruction involving *interactive* learning activities with technology: Tudor Car et al. (2019, ES3) compared traditional textbook- and lecture-based instruction with digital problem-based learning in medical education. The result was a medium-sized positive effect, but only three ESs were synthesized in this effect. Shi et al. (2020, ES2) compared traditional instruction with collaborative, technology-enabled active learning environments, including collaborative problem solving and flipped classrooms with peer collaboration. Although this effect did trend in a positive direction, the ES was nonsignificant.

Comparisons of an *active* nontechnology group with a *constructive* technology group that could also be classified as redefinition were synthesized in nine ESs: Steenbergen-Hu and Cooper (2014, ES4) compared traditional classroom instruction with intelligent tutoring systems, resulting in a small significant effect. In addition, Ozdemir et al. (2018) compared traditional instruction methods with augmented reality applications. Although based on only three ESs from primary studies, the overall effect was large. In medical education, Zeng et al. (2023) compared traditional training for advanced life support with high-fidelity simulations. While finding a medium sized effect on conceptual knowledge (Zeng et al., 2023, ES1), no significant effect on knowledge application was found (Zeng et al., 2023, ES2). Similarly, in the realm of medical education with simulations, Mitchell and Ivimey-Cook (2023) found a medium sized effect in favor of simulations including virtual reality compared to traditional training. In the context of STEM education, Cao and Hsu (2023) compared traditional teaching methods with virtual experiments that simulate experimental operation process or experimental phenomena. They found a small effect in favor of virtual experiments. Specifically focusing on mathematics instruction, Akın (2022) compared traditional mathematics instruction with web-based mathematics instruction that includes drill-and-practice applications, simulations, and intelligent tutoring systems. The TEL condition had a large effect on learning. Also in the STEM context, Gui et al. (2023) compared traditional teaching with digital game-based learning and found a positive and large effect in favor of games. Following a more general approach including a variety of domains (primarily social sciences and STEM) Zheng et al. (2023) synthesized effects of learning analytics intervention in comparison to conventional instructional methods. The authors found large effect of digital problem-based learning (Zheng et al., 2023, ES1) and a medium-sized effect of flipped classroom interventions (Zheng et al., 2023, ES2). The effect of digital game-based learning was nonsignificant, however, only based on two ESs from primary studies (Zheng et al., 2023).

One effect, also stemming from Zheng et al. (2023, ES4), was from a comparison of *active* instruction without technology versus instruction

Table 3
Effects that investigated comparisons of different learning activity levels with descriptions of both technology and nontechnology conditions, assignment to ICAP-inspired SAMR model and ICAP model, measured learning outcome, effect size, and 95 % confidence interval, number of primary effect sizes as well as primary studies included with that effect, and investigations of the homogeneity of the effect.

ES reference	Nontechnology condition	Technology condition	SAMR	ICAP	Learning outcome	ES	95 % CI	Primary ES (studies)	Homogeneity of effect
Hunsu et al. (2016), ES2	Conventional lectures	Clicker-based technologies with multiple-choice questioning	M	P vs. A	Mixed	$g = 0.13$	[0.09, 0.17]	41 (41)	No
Sosa et al. (2011), ES1	Traditional lecture-based instruction	Computer-assisted instruction with instructional tools (keypads or clickers)	M	P vs. A	Conceptual knowledge	$g = 0.33$	[0.12, 0.53]	13 (13)	Not reported
Seyyedrezaei et al. (2022), ES2	Non-technology writing instruction	Collaborative technologies in writing class with peer feedback	M	C vs. I	Application-oriented knowledge	$g = 1.20$	[0.94; 1.45]	34 (34)	No
Chen et al. (2018), ES1	Traditional lecture-based instruction	Flipped classroom	R	P vs. C	Conceptual knowledge	$SMD = 0.47$	[0.31, 0.63]	41 (41)	No
Chen et al. (2018), ES2	Traditional lecture-based instruction	Flipped classroom	R	P vs. C	Conceptual knowledge	$SMD = 0.35$	[0.16, 0.55]	9 (9)	No
Chen et al. (2018), ES3	Traditional lecture-based instruction	Flipped classroom	R	P vs. C	Application-oriented knowledge	$SMD = 3.12$	[−2.22, 8.45]	2 (2)	No
Shi et al. (2020), ES1	Traditional lecture-based instruction	Technology-enabled active learning environments - individual	R	P vs. C	Conceptual knowledge	$SMD = 0.84$	[0.58, 1.09]	19 (19)	Not reported
Sosa et al. (2011), ES2	Traditional lecture-based instruction	Number cruncher: tools to manipulate or analyze data (e.g., SPSS, STATA); providing users with computations and statistical output	R	P vs. C	Conceptual knowledge	$g = 0.34$	[0.06, 0.63]	14 (14)	Not reported
Steenbergen-Hu and Cooper (2014), ES3	Reading printed text	Intelligent tutoring system	R	P vs. C	Conceptual knowledge	$g = 0.50$	[0.22, 0.78]	8 (8)	Yes
Shi et al. (2020), ES2	Traditional lecture-based instruction	Collaborative technology-enabled active learning environments	R	P vs. I	Conceptual knowledge	$SMD = 0.26$	[−0.02, 0.54]	10 (10)	Not reported
Tudor Car et al. (2019), ES3	Traditional learning with textbooks and lectures	Digital problem-based learning	R	P vs. I	Conceptual knowledge	$SMD = 0.67$	[0.14, 1.19]	3 (3)	No
Akın (2022)	Traditional mathematics instruction	Web-based mathematics instruction	R	A vs. C	Application-oriented knowledge	$g = 1.91$	[1.61, 2.22]	32 (32)	No
Cao and Hsu (2023)	Traditional teaching	Virtual experiments	R	A vs. C	Mixed	$d = 0.48$	[0.30, 0.65]	62 (62)	No
Gui et al. (2023)	Traditional training	Digital game-based learning	R	A vs. C	Mixed	$g = 0.91$	[0.58, 1.23]	32 (24)	Not reported
Mitchell and Ivimey-Cook (2023)	Traditional training	Digital technology-enhanced simulation including virtual reality	R	A vs. C	Mixed	$SMD = 0.55$	[0.11, 1.00]	44 (44)	Not reported
Ozdemir et al. (2018)	Traditional methods	Augmented reality application	R	A vs. C	Conceptual knowledge	$d = 0.84$	[0.19, 1.06]	3 (3)	Not reported
Steenbergen-Hu and Cooper (2014), ES4	Traditional classroom instruction	Intelligent tutoring system	R	A vs. C	Conceptual knowledge	$g = 0.38$	[0.21, 0.55]	16 (16)	Yes
Zeng et al. (2023), ES1	Traditional training	high-fidelity simulation-based training	R	A vs. C	Conceptual knowledge	$SMD = 0.71$	[0.51, 0.97]	5 (5)	Yes
Zeng et al. (2023), ES2	Traditional training	high-fidelity simulation-based training	R	A vs. C	Application-oriented knowledge	$SMD = -0.08$	[−0.37, 0.22]	7 (7)	Yes
Zheng et al. (2023), ES1	Conventional methods	Problem-based learning	R	A vs. C	Conceptual knowledge	$g = 0.82$	[0.44, 1.20]	5 (5)	Not reported
Zheng et al. (2023), ES2	Conventional methods	Flipped classroom	R	A vs. C	Conceptual knowledge	$g = 0.72$	[0.04, 1.40],	5 (5)	Not reported
Zheng et al. (2023), ES3	Conventional methods	Game-based learning	R	A vs. C	Conceptual knowledge	$g = -0.30$	[−1.89, 1.29]	2 (2)	Not reported
Zheng et al. (2023), ES4	Conventional methods	Collaborative learning	R	A vs. I	Conceptual knowledge	$g = 1.51$	[0.69, 2.33]	7 (7)	Not reported

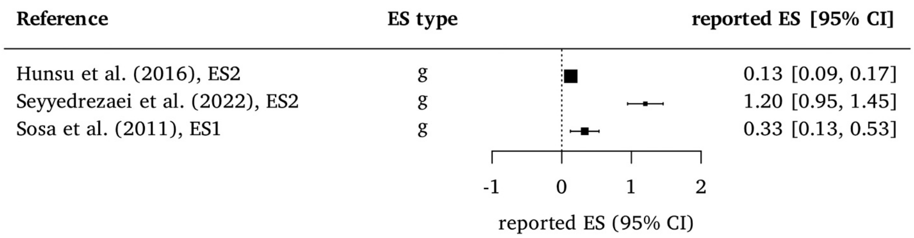

Fig. 6. Forest plot with reported effect sizes (ES) of modifications with digital technologies differentiated by ES type (SMD: standardized mean difference; d: Cohen's d; Hedges' g). The point estimate of the meta-analysis result is represented by a black box. Horizontal lines representing the 95 % confidence intervals, with each end of the line representing the boundaries of the confidence interval.

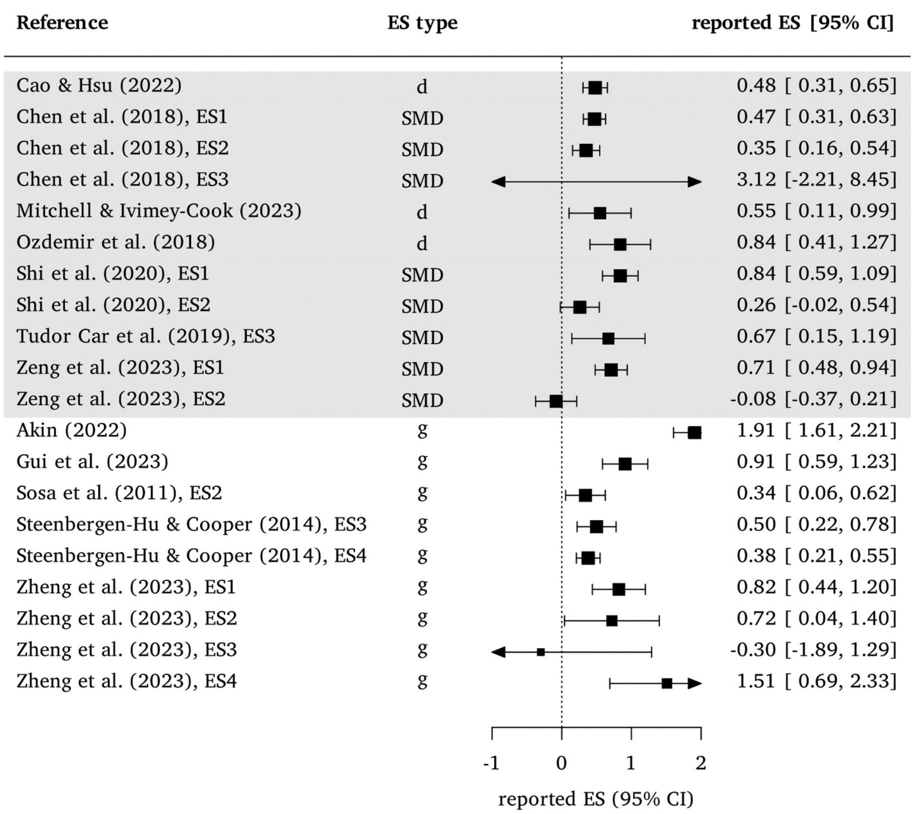

Fig. 7. Forest plot with reported effect sizes (ES) of redefinitions through digital technologies differentiated by ES type (SMD: standardized mean difference; d: Cohen's d; Hedges' g). The point estimate of the meta-analysis result is represented by a black box. Horizontal lines representing the 95 % confidence intervals, with each end of the line representing the boundaries of the confidence interval (in case of extreme values, arrows show that boundaries are located outside of the limits of the visualized range of values).

involving *interactive* learning activities with technology: Conventional instructional methods were compared to digital collaborative learning. The ES was large in favor of TEL. 16 out of 20 effects that reflected redefinitions of learning activities with digital technologies showed significant positive results. These results indicate that redefining learning activities by changing them from shallow learning processes to deep learning processes with the help of digital technologies might be a central mechanism of TEL that can help students reach higher gains in their learning. When comparing the effects of modification with the effects of redefinition, our systematic review was limited to a small amount of data: We found only three eligible modification ESs. Thus, the potential conclusion that redefinition effects are larger than modification effects must be viewed with caution.

3.3. Moderating effect of ICAP-inspired SAMR level: Second-order Meta-analyses

To answer the research question whether the ICAP-inspired SAMR level moderates the effect of digital technology on learning outcomes in higher education, we conducted a second-order meta-analysis using the R-packages 'psychmeta' (Dahlke & Wiernik, 2019) and 'metafor' (Viechtbauer, 2010). To reduce biases by methodological flaws in included meta-analyses, we only included meta-analyses which reported Hedges' *g*. Hedges' *g* corrects Cohen's *d* to address the small sample bias (i.e. the problem that small samples bear a higher risk to overestimate effect sizes; see Borenstein & Hedges, 2019). Since random effects were addressed within the first order meta-analyses and no variation in used type of effect size, a fixed effects model was applied to integrate effect sizes from multiple meta-analyses. Inverse-variance weighting was used to compute summary effects sizes (i.e. the more precise the estimation of an effect size, the higher the weight; see Borenstein & Hedges, 2019). In summary, we included 25 ESs from 16 meta-analyses in the second-order meta-analyses.

The results showed that digital technology has no substantial general effect on learning outcomes in higher education (overall effect size: $g = 0.03$, 95 % CI [0.03, 0.04]; see Fig. 8).

As expected, the effect of digital technology on learning outcomes in higher education was moderated by the level of the ICAP-inspired SAMR model; $Q(3) = 497.40$, $p < .001$: While digital technology used as substitution had no substantial effect on students' learning ($g = 0.01$, 95 % CI 0.01, 0.01]), digital technology used to modify learning activities had a significantly higher though still not substantial effect ($g = 0.15$, 95 % CI [0.12, 0.19]). Digital technology used to redefine learning activities had a large effect ($g = 0.85$, 95 % CI [0.74, 0.97]). In line with the ICAP model, these results support the proposed mechanism of TEL that enhancing learning activities by digital technologies fosters learning outcomes in higher education. In addition, the second proposed mechanism of TEL (facilitating certain learning activities by cognitive support) is also supported by our results: Digital technologies affected learning outcomes in higher education positively if they acted as an augmentation for cognitive support ($g = 0.46$, 95 % CI [0.44, 0.47]). A large proportion of $R^2 = 64.21$ % variance in overall technology use in higher education was explained by the ICAP-inspired SAMR model. About 91 % of the remaining 35.79 % unexplained variance can be potentially explained by other factors beyond the ICAP-inspired SAMR; $Q(21) = 226.83$, $p < .001$, $I^2 = 90.74$ %.

4. Discussion

We conducted a systematic review and second-order meta-analysis of effects from meta-analyses that compared instruction with versus without digital technology in higher education from a learning activity perspective. With this approach, we aimed to provide an overview of how digital technologies are used in teaching in higher education and on the extent to which digital technologies have an impact on students' learning outcomes. Our approach is very different from the commonly employed approaches that focus on the effects of specific digital technologies. To account for the nature of technology use, we used the ICAP model to code the learning activities used in both the technology and nontechnology conditions (see Chi & Wylie, 2014). In addition, when comparing instruction with versus without digital technology, we also distinguished between effects that referred to comparisons of learning activities that were on the same learning activity level versus effects that referred to comparisons of learning activities that were on different learning activity levels. When comparisons of instruction with versus without technology referred to the same level, we differentiated between the use of digital technology as a substitution versus an augmentation of cognitive support for students' learning processes. When comparisons referred to different learning activity levels, we differentiated between modifications that occurred within shallow or deep learning processes and redefinitions that led to major changes in learning activity levels (i.e., moving from shallow to deep learning processes).

Regarding comparisons on the same learning activity level, our results showed that when digital technology was implemented as a substitution, the effects on students' learning outcomes in higher education were nonsignificant. By contrast, all augmentations of cognitive support for learners' cognitive processes had significant positive effects on students' learning outcomes in favor of instruction that employed technology. These results indicate that cognitive support plays a central role in the effectiveness of the use of digital technology. Without the augmentation of such cognitive support, TEL did not positively affect learning.

With regard to the results of the comparisons of different learning activity levels, our results show that the vast majority of these effects led to a significant positive effect on students' learning outcomes. Although we found only three effect size from an investigation of a modification, the results on redefinition highlighted that using digital technologies to help redefine learning activities so that the processes involved in the activities change from shallow to deep might be a central mechanism of TEL that can help students achieve more in their learning.

Our approach of using the ICAP model and an ICAP-inspired SAMR classification helped to reveal the central ways in which digital technologies can affect learning outcomes as well as the conditions under which they do not result in learning gains. We clearly see three groups of studies that can be categorized along the ICAP-inspired SAMR classification: (a) a group of meta-analyses that investigated digital technologies that were being used as substitutes for nontechnology instruction with no significant effects of TEL; (b) a group of meta-analyses that investigated digital technologies that implemented cognitive support for students without changing the learning activity (in comparison with a nontechnology condition) with significant effects on students' learning; and (c) a group of meta-analyses that synthesized effects of implementations that afforded more advanced learning activities through the use of digital technologies, also with significant effects on students' learning. We discuss the three groups of ESs in more detail next.

4.1. Technology-based substitutes for nontechnology instruction do not enhance learning

On the one hand, our results highlight that the use of digital technologies per se does not make a difference in students' learning outcomes in higher education. In line with Clark (1994), a change in the medium of instruction while students engage in the same learning activity with no or an equal amount of cognitive support does not lead to a significant improvement in students' learning outcomes compared with instruction without technology. However, although significant effects of using digital technology as a substitute for nontechnology instruction on learning outcomes are clearly missing, the goal of such implementations can go beyond an increase in the learning outcomes that were measured in the meta-analyses from our review. For example, in the study by

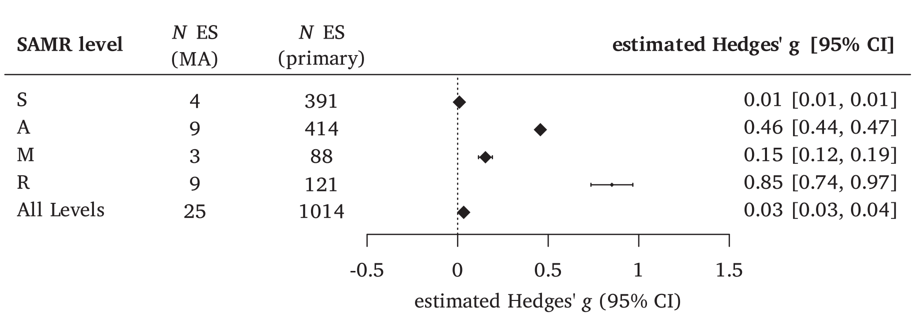

Fig. 8. Forest plot of results from second-order meta-analysis. N ES (MA) specifies the number of ES from meta-analyses included. N ES (primary) specifies the number of ESs from primary studies that are included in this effect. The point estimate of the second-order meta-analysis result is represented by a diamond. Horizontal lines representing the 95 % confidence intervals, with each end of the line representing the boundaries of the confidence interval.

Steenbergen-Hu and Cooper (2014) regarding ES1, the comparison of intelligent tutoring systems with human tutors did not lead to a significant difference between the two groups. This result can be interpreted to mean that technology can indeed be a successful substitute in learning situations in which resources for tutors are low and in which elaborated just-in-time feedback might be more desirable than a delay in feedback from a tutor. In addition, elaborated automated feedback can be used as an additional resource for support that can be provided in practice alongside support from human tutors.

Further, the learning outcomes that result from digital technology substitutes could go beyond the mostly domain-related measures of knowledge and skills: Getting students to use digital technologies or virtual learning environments can be a desired outcome that might not have been captured in meta-analyses but that are essential with regard to the 21st century skills of higher education students (Kirschner & Stoyanov, 2020). Further, based on our approach of systematically reviewing meta-analytic effects, aspects of *the digital condition* (Stalder, 2018) that emphasize that technology changes our behaviors and learning in a fundamental way beyond measured (domain-specific) learning outcomes might not be reflected in the approach we chose to use for our analysis. However, it might be a relevant topic to consider for higher education and students' future careers and life. An awareness of the cognitive-focused learning outcomes in our analysis is important when interpreting the results. The interpretation regarding these cognitive outcomes is very clear: When the goal is to improve students'—mostly domain-specific—cognitive learning outcomes, it will not be possible to contribute to achieving this goal by using teaching with digital technologies as a substitute for nontechnology instruction without changing the afforded learning activities or without systematically implementing cognitive support.

On the other hand, our results clearly point out two directions that can be helpful when using digital technologies to foster students' learning outcomes in higher education: augmenting support for cognitive processes through digital technologies and changing the central learning activity with the help of digital technologies so that deep learning processes are engaged.

4.2. Augmentations that use technology to provide cognitive support enhance learning

Augmenting a certain learning activity by providing cognitive support for the underlying cognitive processes through digital technologies was shown to be effective in fostering students' learning in higher education. According to our results, these augmentations of cognitive support work for all types of learning activities in the ICAP model: scaffolding students by applying dynamic changes to the representation of learning content for better storing of information (Höffler & Leutner, 2007); offering additional cognitive support for storing, activating, and linking when students engage in active learning activities by providing corrective and automated feedback (Viljoen et al., 2019, ES2); supporting the cognitive processes of activating, linking, and inferring during the execution of generative learning activities by implementing scaffolding (Al-Wasy, 2020); and in the context of interactive learning activities, providing support for the cognitive process of co-inferring by implementing scaffolded collaboration (Tudor Car et al., 2019, ES2). These results are in line with theories and related meta-analyses that have emphasized the important role of feedback (Hattie & Timperley, 2007), scaffolding (Belland et al., 2017), and sociocognitive scaffolding (Radkowitsch et al., 2020) in technology-based learning environments. In conclusion, digital technology implementations that do not differ in the extent to which they afford students' learning activities can have a positive effect on students' learning outcomes as long as they include systematic cognitive support for students' learning activities. This pattern of results is in line with our expectations regarding RQ1.

4.3. Redefining learning activities enhances learning

Integrating digital technology into learning contexts offers more diverse teaching and learning opportunities (Hattie, 2009). In our review, a group of meta-analyses that investigated a change in students' central learning activities showed that digital technologies were indeed implemented so that they afforded a higher learning activity level compared with nontechnology instruction and thus afforded more sophisticated learning opportunities to students. In line with the ICAP model (Chi & Wylie, 2014) and in line with our expectations regarding RQ2, the vast majority of these effect sizes showed an increase in students' learning outcomes in higher education. Thus, digital technologies that are implemented so that they increase the level of learning activity as represented in the ICAP model have greater potential to also lead to an increase in students' learning outcomes. In addition, our results suggest that digital technologies might help teachers and designers of technology-rich environments to afford an increase in ICAP levels with the help of digital-technology-based instruction. This idea is in line with research that showed that college students were more likely to engage in constructive learning activities when their teacher used digital technology compared with nondigital instruction (Wekerle et al., 2020).

To answer the question whether this change in learning activity level must take place between shallow and deep learning processes or within one of these two, results of our study have to be viewed with caution as we only found three ES referring to modifications. However, results from the second-order meta-analysis show that while modifications do have an ES below the small threshold, redefinitions show a large ES. We can therefore conclude that a change from shallow to deep learning processes (i.e., from passive or active to constructive or interactive) has great potential to result in significant positive effects on students' learning outcomes. Interestingly, and compared to effects of substitutions, augmentations, and modifications, the ES of redefinitions not only shows the largest ES, but also the largest variance. This may indicate that the contextual conditions of implementing those sophisticated learning activities with digital technologies should be considered and investigated in future research (Sailer et al., 2021).

In conclusion, our results provide support for the ICAP model (Chi & Wylie, 2014). Despite the justified criticism of the SAMR model, our approach of augmenting the SAMR model with a learning activity perspective showed the applicability of the model in the context of TEL when focusing on students' context-specific and cognitive learning outcomes. This is also supported by the results of our second-order meta-analysis that indicate a moderating role of the ICAP-inspired SAMR level on the effect of TEL in higher education. Further, the ICAP-inspired SAMR model explained a large amount of variance of TEL in higher education, supporting its high explanatory power.

4.4. Limitations and future research

The results of this systematic review and second-order meta-analysis need to be viewed in light of several limitations. Some issues in this systematic review are due to the typical limitations of meta-analyses (see Borenstein et al., 2009; Borenstein & Hedges, 2019). First, the reported effects could be biased from the incorporation of poor-quality studies. Although the eligible primary studies used (quasi-)experimental data, preexisting differences were not tested or controlled for in all cases. The effects could be overestimated because studies with large effects are more likely to be published, and published studies are more likely to be included in a meta-analysis. Of the 28 meta-analyses we included, nine did not report on publication bias testing, and four reported that a publication bias was possible (see Table 1). Second, when multiple primary effects are extracted per study, the ESs are not independent, and a study with more effect sizes than others contribute more weight than studies with fewer effect sizes. Third, the models that were chosen for synthesizing the ESs can influence the results. Whereas FEMs assume that the true effect size for all primary studies is identical, and the variances of the ESs are attributed to errors in estimating the ESs, REMs do not assume a true effect and instead estimate the mean of a distribution of effects (Borenstein & Hedges, 2019). For the field of TEL, it is rather naive to assume a true effect, and thus—also in general for the fields of educational sciences and educational psychology—the integration of effect sizes through the REM is regarded as current state-of-the art (Borenstein & Hedges, 2019). Four meta-analyses did not report the type of statistical model they used, and two meta-analysis used FEM (see Table 1). Therefore, the generalization of the findings from these analyses cannot be guaranteed.

There are some other limitations that are grounded in the approach we followed in conducting our systematic review and second-order meta-analysis: First, due to the meta-meta level of this systematic review and second-order meta-analysis, some meta-analyses might have included some of the same primary studies. Therefore, some primary studies may have contributed repeatedly to our findings. However, as the domains and subjects of the meta-analyses included in our study were rather diverse (see Table 1), this limitation likely does not concern a major proportion of the studies. Second, our classification of the ICAP level was based on the descriptions provided in the meta-analyses about the digital technologies or their pedagogical use. These descriptions differed in the level of detail they provided and also led to a large number of studies that were not eligible because of a lack of detail. Our systematic review and second-order meta-analysis clearly show the importance of reporting and considering the learning activities involved in both the experimental and control conditions in primary studies as well as in meta-analyses. Future research (primary studies and meta-analyses) have to consider student learning activities in their research to provide a clearer picture of the effects of TEL and instructional interventions in general. As our systematic review and second-order meta-analysis showed, when investigating the effects of a certain instructional approach, the effect sizes might vary fundamentally depending on the comparison group that was applied in the research. Third, while comparisons within the same ICAP level allowed us to examine the effect of technology in providing cognitive support, comparisons between different ICAP levels did not enable us to distinguish whether the observed effect was due solely to the change in learning activity, or to a combination of this change and additional cognitive support for new learning activities. This ambiguity might also explain the substantial heterogeneity observed in the redefinition category. Conversely, the significantly higher effects observed in redefinitions compared to augmentations underscore that changes in learning activities were indeed pivotal. For a more nuanced understanding of these potentially combined effects, future research could delve deeper into primary studies within meta-analyses, rather than adopting a meta-meta-analytic approach.

Finally, the ICAP model is based on observations of student behavior and student learning products (Chi, 2009). In our study, we applied the ICAP model on the basis of descriptions of either the students' behavior or instruction with or without digital technology as an approximation of students' actual behavior. However, these different kinds of instruction might function as affordances that learners can take advantage of only when certain motivational variables, attitudes, or learning prerequisites are taken into consideration (see Sailer et al., 2021).

4.5. Implications for practice

Our systematic review suggests some recommendations for the use of digital technologies in TEL that go beyond recommendations for specific implementations of digital technologies and that might therefore be helpful for higher education teachers and higher education policy makers. In light of the COVID-19 pandemic, such recommendations are important for providing teachers with central mechanisms that can be applied to improve higher education students' learning outcomes.

When we compared different learning activity levels in our study, the digital technology condition always had the more sophisticated learning activity level, possibly suggesting that it is easier to engage all learners in active, constructive, or interactive learning activities when teaching incorporates digital technology (see Tamim et al., 2011). Also, the effects of the implementations of technology showed a clear positive tendency for digital technology implementations to evoke a change in learning activities. Focusing on ways to include forms of TEL that promote the engagement of all learners in active forms of learning (particularly constructive, and interactive learning activities; Chi & Wylie, 2014) is a central mechanism for improving students' learning. According to our review, digital technologies are a suitable means for achieving this aim.

Another important mechanism that can be derived on the basis of our results is the augmentation of instructional settings with cognitive support for learning activities. Systematically implementing cognitive support with digital technologies can help higher education students improve their learning. The possibilities for implementing such cognitive support for certain learning activities are manifold: Different types of scaffolding and feedback were shown to be effective ways to improve students' learning. In addition, recent advances in the development of digital technologies and learning environments often allow for adaptive and personalized support measures that might further increase the potential for applying cognitive support (Bernacki et al., 2021).

4.6. Conclusion

With this systematic review and second-order meta-analysis, we provide evidence that, just as Clark (1994), Tamim et al. (2011), Wekerle et al. (2020), and Sailer et al. (2021) previously recommended, the relevance of *how* digital technology is used should be the focus instead of which kind of technology is used. A paradigm shift from technology-driven research to educational science-driven research, which takes into consideration the form of instructional support and the learning activities as approximations of cognitive processes, might be helpful for TEL research to further elaborate on the mechanisms that are responsible for how digital technologies might facilitate learning.

Our systematic review of meta-analyses and second-order meta-analysis is a first step toward understanding the mechanisms that describe *how* digital technologies can foster learning in higher education: Digital technologies can provide higher education students with support for cognitive processes (e.g., by implementing scaffolding or feedback). Implementations of systematic cognitive support resulted in positive effects in the meta-analyses included in our study. Further, digital technologies can afford more advanced learning activities to higher education students. Our review of meta-analyses showed that implementing a broad variety of more advanced learning activities with the help of digital technologies is an effective way to enhance students' learning.

These results highlight the importance of considering learning activities in TEL research and adopting such a perspective when investigating effects of digital technologies. Further, they can be seen as providing strong empirical support for the ICAP model (Chi & Wylie, 2014) in the context of TEL in higher education. By combining a learning activity perspective with an ICAP-inspired SAMR interpretation to conduct our review, we offer a successful advancement of theory-building to categorize effect sizes in TEL research and derive recommendations for TEL in higher education.

5. Ethical clearance statement

In this study we collected and synthesized data from previous studies in which informed consent has already been obtained by the investigators of primary studies. Thus, our study does not require an ethics approval.

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CRediT authorship contribution statement

Michael Sailer: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Rebecca Maier:** Data curation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing. **Sonja Berger:** Investigation, Resources, Validation, Writing – review & editing. **Tamara Kastorff:** Investigation, Resources, Validation, Writing – review & editing. **Karsten Stegmann:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Software, Supervision, Visualization, Writing – review & editing.

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