

## **Using digital technology to promote higher education learning: The importance of different learning activities and their relations to learning outcomes**

Digital technologies can have positive effects on student learning in higher education. Based on the ICAP framework, they should be particularly effective when teachers use them to encourage student engagement in constructive and interactive as opposed to passive and active learning activities. Using a sample of 381 higher education students, we investigated if student engagement in these activities depends on whether technologies are implemented in class or not, and how engagement in these activities affects learning outcomes. Results indicated that when technologies were implemented in class, students felt encouraged to engage in more constructive, but also in more passive and active activities as compared to when no technologies were used. Furthermore, student engagement in active, constructive, and interactive activities was positively associated with learning outcomes.

Keywords: technology-supported learning, ICAP, TPACK, learning activities

## **Problem statement**

Not just since the Covid19 pandemic, the digitalization of higher education systems has been considered a powerful means to promote student learning. However, promoting student learning does not appear to be a question of *what* types of technology are used, but rather *how* technology is used (Chien et al., 2016; R. F. Schmid et al., 2014; Tamim et al., 2011). Thus, higher education teachers' knowledge about how to effectively use technology in their courses (Technological Pedagogical Content Knowledge, or, in short: TPACK; Koehler & Mishra, 2008; Mishra & Kohler, 2006) seems to play a crucial role for a successful implementation of technology in higher education classrooms. In line with constructivist, learner-centered assumptions, the Interactive Constructive Active Passive framework (ICAP; Chi, 2009; Chi et al., 2018; Chi & Wylie, 2014) proposes that the effectiveness of digital technologies depends on the degree to which they prompt student engagement in constructive and interactive learning activities. Even though technology use in the higher education context has been of interest recently (Bond et al., 2018; Galanek et al., 2018; Marcelo et al., 2015; Newman & Beetham, 2017; Newman et al., 2018; U. Schmid et al., 2017), it remains unclear whether teaching in higher education proves to be more learner-centered when technology is used compared to when it is not used. In addition, up to now, studies in the context of the ICAP framework have only considered associations between different types of learning activities on the one hand and students' acquisition of domain-specific knowledge on the other hand, but not yet of 21<sup>st</sup> century cross-domain skills (i.e., skills and strategies such as self-regulated learning that have a broad range of applications across different domains; Vogel et al., 2017) relevant to students' adaptation to future work environments.

Given this background, we pursued two research goals with the present study. Firstly, we investigated the degree to which higher education students actually feel encouraged by

their higher education teachers to engage in different types of learning activities in technology-supported course phases as compared to non-technology-supported course phases. The second aim was to explore the effects of students' engagement in different types of technology-supported and non-technology-supported learning activities on students' acquisition of domain-specific knowledge and cross-domain skills.

### **Higher education teachers' TPACK**

As meta-analytic results illustrate (Chien et al., 2016; R. F. Schmid et al., 2014; Tamim et al., 2011), an important precondition for positive effects of technology use on students' learning outcomes seems to be higher education teachers' knowledge about how to effectively implement technology in higher education courses. To this end, Mishra and Koehler (2006, also Koehler & Mishra, 2008) introduced the *TPACK* framework. TPACK refers to teachers' integrated knowledge of technological (TK), pedagogical (PK), and content knowledge (CK) that goes beyond each of the individual (TK, PK, CK) and combined knowledge components (PCK, TCK, TPK). As such, it is understood as knowledge on how different types of digital technologies can enhance or impede different representations of content as well as teaching and learning processes.

The TPACK framework has gained a lot of attention and recognition in the teacher research community (Herring et al., 2016). As Harris et al. reported in 2017, more than 1.200 publications were based on the TPACK framework thus far. Most TPACK-inspired research until now can be characterized by the three following aspects:

Firstly, a lot of research has been dedicated to determine how well TPACK is developed among- in- and pre-service teachers. However, research on higher education teachers' TPACK is still rare (Chai et al., 2016; Herring et al., 2016; Willermark, 2018; Wu,

2013). Secondly, research on TPACK is predominantly based on self-report measures (Chai et al., 2016; Koehler et al., 2012; Voogt et al., 2013; Willermark, 2018) that assess teachers' knowledge outside of actual teaching situations. Much less is known on how teachers bring their TPACK to bear in their actual classroom practice (Willermark, 2018). The studies that looked into how technology is actually used in higher education classrooms (Bond et al., 2018; Galanek et al., 2018; Marcelo et al., 2015; Newman & Beetham, 2017; Newman et al., 2018; U. Schmid et al., 2017), in turn, mostly focused on technology-supported teaching itself, i.e. without comparing it to non-technology-supported teaching at the same time. Yet, in order to clarify whether the potentials of technology are actually used in higher education settings, it is necessary to take intrapersonal differences between technology- and non-technology-supported teaching into account. And thirdly, with its emphasis on the role teachers' TPACK plays for students' acquisition of domain-specific knowledge, the TPACK framework does not provide any guidance on the question how teachers can use technology in classrooms in order to enhance students' 21<sup>st</sup> century skills (Brantley-Dias & Ertmer, 2013), such as creative thinking and collaborative learning (Partnership for 21st Century Learning, 2015, 2019). This is surprising, given that digital technologies are often said to hold particular potentials for the acquisition of such skills (D. Clark et al., 2010). Against this background, many researchers suggest to complement the TPACK framework by adopting a more learner-centered, constructivist perspective on TPACK (Angeli & Valanides, 2009; Chai et al., 2013; Koh et al., 2017; Olofson et al., 2016). Such a perspective has recently been developed by Chi and colleagues in their so-called *ICAP* framework (Chi, 2009; Chi et al., 2018; Chi & Wylie, 2014), which will be described in the next section.

### **A learning activity perspective on technology-supported teaching**

The ICAP framework of Chi and Wylie (2014) differentiates between four types of overt learning activities and associated knowledge-change processes and their impact on the subsequent acquisition of domain-specific knowledge: passive, active, constructive, and interactive. Learning activities are understood as *passive* when no overt learning behavior of a student can be observed while dealing with the learning material at hand (e.g., watching an online video). At the cognitive level, this type of engagement is assumed to mainly afford isolated information-storing processes and allows for not much more than mere recall of information, particularly in identical contexts. Yet, transfer and application of this knowledge to new situations will typically still be difficult. An *active* type of engagement refers to motoric and physical interactions with the learning material (e.g., pausing or forwarding an online video). Active learning activities are believed to allow students to integrate new information with their prior knowledge and existing schemes. Thus, active learning activities are assumed to facilitate an application of that knowledge at least in contexts that are similar to the ones in which this knowledge was acquired. *Constructive* activities involve the creation of new knowledge that goes beyond the initially provided learning material (e.g., creating a concept map of online video content). At the cognitive level, an engagement in constructive learning activities is thought to hold the potential to result in inferring new knowledge. This, in turn should often allow for transfer of knowledge to new contexts. Finally, learning activities are defined as *interactive* when two or more learning partners create new learning content together by taking turns during dialogue and thereby referring to each other's utterances (e.g., writing a review of an online video in a small group). This type of engagement is supposed to facilitate learners to infer new knowledge due to the activated and integrated knowledge acquired from the learning material, and due to the additional input

provided by the learning partner (e.g., ideas, elaboration, feedback etc.). Optimally, co-inferring of knowledge from discussion should not only allow for a transfer of this knowledge but also a co-creation of new learning products.

As, according to Chi and Wylie (2014), the cognitive processes become increasingly more elaborated from passive to interactive, the ICAP framework leads to the following ICAP hypothesis: Interactive learning activities should facilitate the acquisition of domain-specific knowledge to a higher degree than constructive learning activities. Constructive learning activities in turn should facilitate the acquisition of domain-specific knowledge to a higher degree than active learning activities. And finally, active learning activities are expected to be stronger associated with the acquisition of domain-specific knowledge than passive learning activities.

Following the ICAP hypothesis, it would be desirable if higher education teachers used technology in their courses in a way that encourages students to engage in more constructive and interactive activities than in active and passive activities. In a large-scale study in Germany, Sailer et al. (2018) asked higher education students to assess to what extent their teachers encouraged them to engage in the different types of learning activities proposed by Chi and Wylie (2014) when technology was used in courses. Over half of the students reported their teachers to at least frequently encourage an engagement in passive learning activities, followed by active learning activities. In contrast, only around one out of ten students indicated their teachers to encourage them to engage in constructive and interactive learning activities.

In line with these results, in a large-scale study in Spain, Marcelo et al. (2015) found higher education teachers to very frequently use technology-supported presentations, followed by technology-supported demonstrations and videos. Note that all these activities

typically entail a rather passive role of students. Constructive learning activities, such as the production of digital resources by students, an engagement in complex problem-solving activities, or self-assessment exercises were much rarer. The same was true for interactive learning activities such as collaborative work and the use of discussion forums. Also, a representative German survey on technology-supported learning (U. Schmid et al., 2017) indicated that more than half of the surveyed higher education teachers frequently use technology to present content. But only around one third have students frequently actively work with certain software or work collaboratively. In addition, almost none of the teachers use technology frequently for the moderation of discussions. Similar results were obtained by Newman et al. (2018) with a UK teacher sample.

Taken together, these findings cast doubts on higher education teachers' abilities to use the potentials of digital technology to promote high-quality student learning. Nevertheless, it remains unclear whether higher education teachers engage their students in more high-level learning activities when they use digital technology compared to when they do not in their courses. For the secondary school context, the SITES 2006 study indicated that in many of the participating countries, mathematics and science teachers followed more constructivist teaching principles when they use digital technologies compared to their overall teaching practices (Law & Chow, 2008). Yet, corresponding evidence at the higher education level appears to be missing.

### **Relations between different (technology-supported) learning activities and the acquisition of domain-specific knowledge and cross-domain skills**

Over the past years, first empirical support in favor of the ICAP hypothesis has been found. However, relations between an engagement in the different learning activities and students'

learning outcomes have so far been limited to the acquisition of domain-specific knowledge. First of all, the ICAP hypothesis was validated by a reanalysis of around 40 existing experimental and classroom studies in school and higher education settings (Chi, 2009; Chi and Wylie, 2014). However, the included studies only compared some types of learning activities (typically pair-wise), not all. Furthermore, Menekse et al. (2013) conducted two studies within higher education. In the first study, they investigated all types of (non-technology-supported) learning activities in a laboratory setting. In the second study, (non-technology-supported) active, constructive, and interactive learning activities were compared in a classroom setting. Results demonstrated that participants' domain-specific knowledge increased from passive to active to constructive to interactive learning activities in the laboratory setting. In the classroom setting, Menekse et al. (2013) mostly found an engagement in interactive learning activities to be superior than an engagement in active learning activities, but not an engagement in constructive learning activities. However, to our knowledge, no other studies in higher education have systematically investigated the differential effects of the four (non-technology-supported) learning activities in classroom settings so far. Thus, further empirical evidence on whether the ICAP hypothesis holds true in higher education classroom contexts is still pending.

As the instructional use of technology seems to be more relevant than the type of technology used to promote learning (Chien et al., 2016), we argue that the ICAP hypothesis should also apply to technology-supported learning activities. Evidence comes from two empirical studies. First, Wang et al. (2016) analyzed the association of the types of higher education students' contributions in a discussion forum and their learning outcome. They found students' constructive and interactive contributions (measured as one factor) to be related to learning outcome more closely than their active contributions. In a second study,

Henderson (2019) investigated the relations of an engagement in passive, constructive and interactive learning activities and learning outcome integrated within a technology-enhanced quiz environment (clicker system). Results illustrated that student engagement in constructive and interactive learning activities predicted learning outcomes better than student engagement in passive learning activities. However, only an engagement in interactive learning activities emerged as a significant predictor. Thus, these findings seem to provide support for the ICAP hypothesis in the higher education context. Yet, none of these two studies included all types of learning activities. Therefore, in the present study we investigated the degree to which the ICAP hypothesis (Chi and Wylie, 2014) applies to the acquisition of domain-specific knowledge in classroom settings in higher education for non-technology-supported as well as technology-supported learning activities.

Yet, the acquisition of domain-specific knowledge is only one out of several possible and desired outcomes of higher education. Over the past years, both researchers and policy-makers consistently argued that students in higher education are not only expected to acquire domain-specific knowledge in order to prepare for their future work environment, but to also acquire so-called 21<sup>st</sup> century skills (Partnership for 21st Century Learning, 2015, 2019). Following Vogel et al. (2017), we will label such skills *cross-domain* skills.

Indirect evidence that the ICAP hypothesis might not only hold true for the acquisition of domain-specific knowledge, but also for the acquisition of cross-domain skills comes from research on problem-based learning (PBL). For example, a meta-analysis by Leary (2012) revealed a positive moderate effect of PBL on students' self-regulated learning compared to lecture-based approaches. Since PBL is described as an approach that particularly aims at actively engaging students in problem solving (very often in groups; see Hmelo-Silver, 2004), these effects might be attributed to a high learner engagement in

constructive and interactive activities. However, results do not indicate to which degree differences between constructive and interactive learning activities are to be expected.

Further, in two meta-analyses, Chen et al. (2018) and Lou et al. (2001) found a moderate effect of computer-supported collaborative learning (CSCL) on students' cross-domain skills (like collaboration and metacognitive strategies), as compared to individual technology-supported learning. As with PBL though, results on the effects of CSCL only point to differences between interactive and all other three types of learning activities. Hence, on the basis of these results, no certain claims about differential effects between constructive, active, and passive learning activities on the acquisition of cross-domain skills can be made.

In summary, prior research illustrates that the ICAP hypothesis might apply to an engagement in technology-supported and non-technology-supported learning activities. Furthermore, there is preliminary evidence that the ICAP hypothesis might not only apply to the acquisition of domain-specific knowledge, but also to the acquisition of cross-domain skills in the context of higher education. Yet, direct evidence for these effects appears to be lacking so far.

### **Research questions and hypotheses**

We investigated whether higher education students feel encouraged to engage in more constructive and interactive learning activities during technology-supported course phases in higher education compared to non-technology-supported phases. Furthermore, we tested whether the ICAP hypothesis (Chi and Wylie, 2014) can be validated in higher education technology-supported classroom settings and whether it would be applicable to not only the acquisition of domain-specific knowledge, but also the acquisition of cross-domain skills. We therefore investigated the following two research questions:

- (1) What are the effects of technology-supported vs. non-technology-supported teaching phases on the types of learning activities students feel encouraged to engage in in higher education?

Based on Law and Chow (2008), we assumed that during technology-supported teaching phases, students would feel encouraged to engage in more constructive and interactive learning activities and in less passive and active learning activities than during non-technology-supported teaching phases (H1).

- (2) To which degree is student engagement in passive, active, constructive, and interactive learning activities during technology-supported and non-technology-supported teaching phases associated with students' acquisition of domain-specific knowledge and cross-domain skills?

Based on the ICAP framework and empirical evidence reported by Chi and Wylie (2014) as well as Menekse et al. (2013), we assumed that the association between non-technology-supported learning activities and domain-specific knowledge would increase from passive to interactive learning activities (H2a). Based on the results of Wang et al. (2016) and Henderson (2019), we expected a similar pattern for technology-supported learning activities (H2b).

Based on research on PBL (Leary, 2012) and CSCL (Chen et al., 2018; Lou et al., 2001), we further expected that the association of technology-supported and non-technology-supported learning activities with cross-domain skills would also increase from passive to interactive learning activities for cross-domain skills (H2c).

## **Method**

### ***Sample***

We recruited pre-service teachers from a German university to participate in the study at the end of the university term 2016/17 (January/February 2017) within a larger course evaluation study. Out of the 577 course attendees taking part in the course evaluation study of 30 courses, 381 participated in our study part (equaling 66%). All participants were pre-service teachers in their 4.69<sup>th</sup> ( $SD = 2.44$ ) term. Their average age was 23.17 ( $SD = 3.94$ ) years and 79.2% reported being female (20.8% male). Participants filled out a questionnaire concerning the respective course they attended. Altogether the sample consisted of participants from 30 different courses. All courses were administered face-to-face. Some of the courses were enhanced by online elements. Courses were situated within a wide range of areas of study. Most of the courses were situated in the social sciences (social sciences: 76.7%, languages: 20.0 %, STEM: 16.7%, humanities: 10.0 %). 26.7% of these courses were interdisciplinary and thus addressed two areas of study. The number of study participants in the different courses ranged from 2 to 28 participants ( $M = 12.70$ ,  $SD = 7.73$ ). In each course, between 20% to 100% out of the course attendees participated.

### ***Instruments***

Course instructors administered the study within their respective courses. They received written instructions on how to administer the questionnaires. The study was conducted in the third from last or second last course session of the term. Course instructors were requested to allow students to work on the questionnaire for about 30 minutes. The paper-pencil questionnaire consisted of three parts. The first part included demographic questions and further questions with regard to the evaluation of the respective course that were not used in

this study. In the second part, participants were first asked to rate the degree to which they felt encouraged to engage in a range of different learning activities *in phases in which technology was used* within the particular course they attended. After that, the same activities were presented to have participants estimate the degree to which they felt encouraged to engage in these activities *in phases in which no technology was used*. In the last step, participants were asked to assess the amount of domain-specific content knowledge as well as a set of cross-domain skills they have acquired by participating in the course. All items can be found in the electronic supplement.

#### *Engagement in technology-supported and non-technology-supported learning activities*

To assess participants' engagement in the different learning activities in phases with and without technology support, we developed an item pool of 21 items on the basis of the ICAP framework by Chi and Wylie (2014). We asked four independent experts highly familiar with the ICAP framework to match each of the items to one type of learning activity (passive, active, constructive, or interactive). Raters' judgments indicated that most of the items fit well to the learning activity they were intended to measure, while a few items might have tapped into more than one type of learning activities. Therefore, we excluded five items. The final items that referred to student engagement in technology-supported course phases were introduced by the stem "By means of the stated digital technologies I was encouraged to...". "Stated digital technologies" in the stem concerned the used digital technologies in the respective course, which participants were asked to state in an introductory question. Examples of digital technologies were made in order to create a common understanding of the term (namely laptop, smartphone, interactive whiteboard, PowerPoint, YouTube, WhatsApp). Items on non-technology-supported learning activities were introduced by the

stem “In phases in which no digital technology was used, I was encouraged to...”. Out of the final 16 items, which were identical for technology-supported and non-technology-supported course phases, three items represented *passive learning activities* (e.g., “read content”), four items *active learning activities* (e.g., “underline text passages”), five items *constructive learning activities* (e.g., “compare content”), and four items *interactive learning activities* (e.g., “explain content to each other”). The items were presented in a mixed sequence and were to be answered on a Likert-type scale from *never* (1) to *very often* (5). All internal consistencies were acceptable to good (see Table 2).

To confirm their factorial structure and the distinctness of the four learning activities, we conducted confirmatory factor analyses for technology-supported and non-technology-supported learning activities. We found a four-factor model distinguishing between passive, active, constructive, and interactive learning activities to fit the data well (technology-support: CFI=.92, TLI=.90, SRMR=.05, non-technology-support: CFI=.94, TLI=.92, SRMR=.05) and significantly better than alternative models in which we combined the measured knowledge facets to form 3- or 2-factor models or a general 1-factor model (all  $\Delta\chi^2 > 45.23, p < .001$ ).

#### *Domain-specific knowledge*

Students’ self-rated acquisition of *domain-specific knowledge* was assessed with four items that were developed based on Krathwohl’s revised learning taxonomy (2002) for deep learning goals, which include the analysis, evaluation, and creation of content (e.g., “This course enabled me to analyze the most important course content.”). Items were measured on a Likert-type scale from *don’t agree at all* (1) to *totally agree* (5). The internal consistency of the scale was good (see Table 2)).

### *Cross-domain skills*

Due to a lack of economic cross-domain skill scales for the higher education course context (existing inventories like LASSI work with 10 or more scales; see Weinstein et al., 2016), we measured cross-domain skills by 15 self-developed items that referred to three types of strategic knowledge: *metacognitive strategies*, *motivational strategies*, and *collaboration strategies*. Specifically, *metacognitive strategies* (e.g., “In this course, I have learned how to set learning goals for myself.”) were measured with five items focused on skills related to planning (e.g., goal setting), monitoring (e.g., assess own knowledge), and regulation (e.g., selecting adequate learning strategies) of learning (Boekaerts, 1999; Pintrich, 2000; Schiefele & Pekrun, 1996). *Motivational strategies* (e.g., “By means of this course, I have learned how to make the (learning) content interesting for me.”) were measured with five items focused on the interest activation, monitoring of interest, and motivation and task persistence, which are considered as important factors for students’ regulation of motivation (Pintrich, 2000; Wolters, 1998). Finally, *collaboration strategies* (e.g., “In this course, I have learned to argue for my point of view in discussions.”) were measured with five items focused on productive communication (e.g., by mutual attention and respect; H. Clark, 1996; or conversation rules; O’Conaill & Whittaker, 1997) and an adequate transmission or construction of knowledge (e.g., by adequate arguments; Wecker & Fischer, 2014). For all items, a Likert-type scale from *don’t agree at all* (1) to *totally agree* (5) was used. The internal consistencies of all three scales were good (see Table 2).

In order to validate the factor structure of domain-specific knowledge and cross-domain skills as learning outcomes, we performed confirmatory factor analyses. A four-factor model distinguishing between domain-specific knowledge, metacognitive strategies, motivational strategies, and collaboration strategies fitted the data well (CFI=.96, TLI=.95,

SRMR=.04) and significantly better than alternative models in which we combined the measured knowledge facets to form 3- or 2-factor models or a general 1-factor model (all  $\Delta\chi^2 > 15.24, p < .01$ ).

### *Statistical analyses*

As individual-level student answers on their learning activities (level 1) nested in courses (level 2) are not independent from each other (Hox et al., 2010), a multi-level approach is required to adjust for dependencies of observations (e.g., due to different instructional approaches of teachers). Small intraclass correlations of .05 can already lead to biased results in conventional regression analyses (Cohen et al., 2003, p. 538). Therefore, we conducted two-level modeling to answer our research questions.

Specifically, Wald  $\chi^2$ -tests were used to test for differences regarding technology-supported and non-technology-supported learning activities. To test the effects of learning activities on learning outcomes, we conducted eight two level regression models. In four of the regression models, technology-supported passive, active, constructive, and interactive learning activities served as predictors at the student level and domain-specific knowledge, metacognitive strategies, motivational strategies, and collaboration strategies were considered as outcome variables at the student level. In the other four regression models, non-technology-supported passive, active, constructive, and interactive learning activities were used as predictors at the student level and again domain-specific knowledge, metacognitive strategies, motivational strategies, and collaboration strategies were included as outcome variables at the student level. Predictors were used at the student level as the reliabilities of course means for the learning activities (ICC2) were rather poor indicating that students tended to perceive learning opportunities offered by the teacher differently, particularly for

non-technology-supported learning activities (see Table 1). To analyze to what degree the effects of the different types of learning activities on learning outcomes differ, confidence intervals (95%) were computed.

All multi-level analyses were performed with Mplus 8 (Muthén & Muthén, 2017) using MLR as an estimator and grand-mean centered predictors. Missing values due to item non-response occurred for around 1.1% of the answers and were dealt with mode-based using the expectation-maximization algorithm (Peugh & Enders, 2004). [Table 1 near here]

## **Results**

### *Descriptive results*

Table 2 illustrates descriptive statistics for technology-supported and non-technology-supported learning activities as well the different learning outcomes. The means of the learning activities ranged around the theoretical scale average except for technology-supported passive learning activities, for which we observed the highest mean. It appears that in total, students in higher education courses were encouraged to engage in all different types of learning activities. The average means for all learning outcomes revealed that in their higher education courses, students perceived themselves to acquire not only domain-specific knowledge but also cross-domain skills. The medium to high variances suggest that students' perceptions differed substantially between individuals [Table 2 near here].

The low intraclass correlations for learning activities and learning outcomes suggest that the configuration of learning activities and learning outcomes were not strongly course-specific (see Table 1). However, the calculation of design effects indicated the necessity to take the variance caused by the course level into account (suggested design effect:  $> 2$ ; Muthén & Satorra, 1995; see Table 1).

***Differences between technology-supported and non-technology-supported learning activities***

Descriptive statistics are illustrated in Table 2. Wald  $\chi^2$ -tests revealed statistically significant, small to large differences between technology-supported learning activities and non-technology-supported learning activities for passive, active, and constructive learning activities (Wald  $\chi^2_{\text{passive}} = 262.52, p < .001$ , Cohen's  $d = 1.49$ ; Wald  $\chi^2_{\text{active}} = 17.32, p < .001$ , Cohen's  $d = 0.30$ ; Wald  $\chi^2_{\text{constructive}} = 49.78, p < .001$ , Cohen's  $d = 0.55$ ). Students reported all these activities as having been stimulated more often during technology-supported phases than during non-technology-supported phases. Regarding interactive learning activities, we found no significant differences between technology-supported and non-technology-supported learning phases (Wald  $\chi^2_{\text{interactive}} = 0.03, p > .05$ ).

***Effects of technology-supported and non-technology-supported learning activities on learning outcomes***

The results of the multilevel regression analyses are illustrated in Table 3 [Table 3 near here]. Technology-supported as well as non-technology-supported passive learning activities were neither found to be significant predictors for the acquisition of domain-specific knowledge nor for the acquisition of cross-domain skills. Active learning activities were significant predictors for all learning outcomes when they were supported by technology, but not when no technology support was present, with the exception of metacognitive strategies. In contrast, significant effects of non-technology-supported constructive learning activities were rather consistent with regard to the different kinds of learning outcomes (for domain-specific knowledge, metacognitive strategies, and motivational strategies, but not for collaboration

strategies) and also occurred consistently for technology-supported constructive learning activities with regard to domain-specific knowledge as well as all cross-domain skills. And finally, technology-supported as well as non-technology-supported interactive learning activities were the most powerful significant predictors for the acquisition of domain-specific knowledge and cross-domain skills (except for motivational strategies in the case of non-technology-supported interactive learning activities).

Concerning the regression weights, 95%-confidence intervals showed that an engagement in active technology-supported learning activities predicted the acquisition of metacognitive and motivational strategies significantly better than an engagement in passive learning activities (see Table 3 and Figure 1). Also, regression weights of interactive learning activities were statistically significantly larger than those of passive learning activities for all three cross domain skills in the case of technology-supported learning activities and at least for collaboration strategies in the case of non-technology-supported learning activities. A significant increase from passive to constructive technology-supported learning activities only occurred in the case of motivational strategies. And finally, a significant increase from active to interactive non-technology-supported learning activities could only be detected for collaboration strategies. Other statistically significant increases could not be observed [Figure 1 near here].

## **Discussion**

In this study, we aimed to move from a solely technology-oriented to a more learner-oriented study approach to get a more nuanced picture of the course-based use of technology and its effects on students' learning outcomes in higher education. We investigated the degree to which higher education students feel encouraged to engage in different learning activities in

technology-supported teaching phases compared to non-technology-supported teaching phases. We also looked into the associations of their self-reported engagement in different types of learning activities and students' perceived acquisition of domain-specific knowledge and cross-domain skills. To that end, we built on a learner-centered reference model (ICAP framework; Chi & Wylie, 2014) and transferred it to the field of technology-supported teaching in higher education.

With regard to the differences of technology-supported and non-technology-supported learning activities, students reported being more strongly engaged in passive, active, and constructive learning activities in course phases in which technology support was present rather than when it was absent. The engagement in interactive activities did not seem to be affected by the presence or absence of technology support. Therefore, hypothesis 1, which proposed that technology use would promote student engagement in more high-quality learning activities, could only partially be supported. Teachers' use of technology in higher education seems to particularly encourage students to engage in constructive learning activities as compared to when they do not use technology, which is a promising result from an ICAP point of view (Chi & Wylie, 2014). However, a comparable pattern was not found to be true for interactive learning activities.

This is partly in line with the results of Law and Chow (2008) who showed that secondary school teachers often move away from traditional teaching (e.g., presenting information) and towards constructivist teaching approaches when using technology support compared to when they do not. However, the activity dimensions that Law and Chow (2008) used did not comply with the ICAP categories, which may be a reason for the different effects. Also, the context (higher education in contrast to secondary school context) might have played an important role. In the context of higher education, Marcelo et al. (2015) and

U. Schmid et al. (2017) pointed to the dominant use of digital presentations (which might mainly trigger an engagement in passive activities) and the work with digital software (which might mainly trigger an engagement in constructive activities). This might explain the relatively high values for constructive, but also passive technology-supported learning activities that we observed in the current study. Reasons for this predominant pattern can be found in the IT infrastructure that still mainly addresses a lecture-style and individual use of technology or in the ignorance of higher education teachers about its capabilities.

Furthermore, a lack of IT support for matters of teaching and learning seems to be an issue that has to be taken care of (Sailer et al., 2018). Also, previous research has shown that at least in Germany, many higher education teachers in general follow an instructional approach (Lübeck, 2009) that might mainly afford an engagement in passive and constructive activities. Nevertheless, based on the study of Sailer et al. (2018), an even higher degree of active learning activities as compared to constructive learning activities might have been expected as well. Still, comparisons may only cautiously be made as in all of the outlined studies, non-technology-supported learning activities were not contrasted with technology-supported learning activities. In consequence, it stands to reason that the potentials of technology in terms of encouraging students to perform high-quality learning processes might still only partially be used.

With regard to the effects of the different learning activities on students' acquisition of domain-specific knowledge and cross-domain skills, interactive learning activities had the strongest relations, while we found no relations between passive learning activities and learning outcomes at all. Instead, we observed a significant increase of effects from passive learning activities to the other learning activities for some of the learning outcomes, but not consistently across all the types of learning activities. Thus, hypotheses 2a, 2b, and 2c can

partially be accepted and seem to correspond to other classroom studies in higher education that mostly found differential associations of different types of learning activities and domain-specific knowledge (Menekse et al., 2013; Henderson, 2019; Wang et al., 2016). By and large though, these results seem to support the ICAP hypothesis (Chi & Wylie, 2014) and are in line with findings from PBL (Leary, 2012) as well as CSCL (Chen et al., 2018). As a result, in higher education courses it should prove effective if higher education teachers design their courses in ways that encourage their students to particularly engage in (technology-supported) interactive learning activities in contrast to the predominantly observed engagement in (technology-supported) passive learning activities.

Further, we found more statistically significant effects of technology-supported learning activities on learning outcomes than of non-technology-supported learning activities. Also, technology-supported learning activities explained more variance in the learning outcomes than non-technology-supported learning activities, at least descriptively. This might be due to reasons such as students' beliefs regarding the effectiveness of technology. In their meta-analysis, R. F. Schmid et al. (2014) observed a small, significant effect of technology use in higher education in comparison to no technology use on students' attitudes in terms of their satisfaction with the course and their evaluation of their learning gains. Also, in the US-based yearly ECAR large-scale study by Brooks and Pomerantz (2017) around 80% of students indicated that they learned most in technology-supported courses (ranging from at least one online component to complete online courses). In addition, between 70% and 80% of students stated that technology helped them to acquire domain-specific knowledge and to build relevant cross-domain skills (Brooks, 2016). Thus, it seems that students tend to perceive technology as an effective mean to enhance their learning, which might consequently moderate the relationship between encouraged learning activities and perceived

learning outcomes. Therefore, students' beliefs should be considered in future studies as a possible moderator variable.

With respect to the replicated main ICAP ideas, it seems necessary to facilitate teachers' knowledge of technology-supported learning activities that afford effective knowledge construction processes on the side of students. More concretely, teachers should learn about ways to use technology to encourage students to move from more passive learning activities (mostly digital presentations) to constructive learning activities (e.g., constructing concept maps) and interactive learning activities (e.g., create an explanation video in small groups). Consequently, higher education teachers should be supported by their institution in various ways (Fabian et al., 2019). One promising approach might be to offer professional development in order to develop teachers' TPACK. Given the importance of pedagogical knowledge in order to develop TPACK (Backfisch et al., 2020; Lachner et al., 2019), we suggest professional development courses to go beyond standalone technology courses and particularly concentrate on ICAP as a learner-centered model. Also, such an approach might need to be more sustainable than a single ICAP-focused online module in the light of its modest outcomes (Chi et al., 2018). Furthermore, (higher education) teachers' conceptions of interactive learning activities should be specifically addressed, as they seem to prevent teachers from creating more higher-order learning environments (Chi et al., 2018). To address these challenges, in research on higher education teachers' TPACK development design approaches have gained considerable attention (Mourlam, 2017). These approaches are mainly based on the constructivist Learning Technology by Design approach (Koehler et al., 2004; Koehler & Mishra, 2005) in which higher education teachers and students collaboratively develop a technology-enhanced course within a course setting. It incorporates elements like collaborative learning, which also plays a central role in the ICAP framework.

Thus, the development of a design-based professional development for higher education teachers that incorporates the ICAP based design guidelines could be a promising direction to follow.

### **Limitations and conclusion**

Our study is among the first to investigate differences between technology-supported and non-technology-supported learning activities and their effects on students' perceived domain-specific knowledge as well as cross-domain skills. Also, the results can be well interpreted on the basis of related research. However, several factors have to be addressed that might limit the explanatory power of the study.

First, due to our small sample size it was not possible to include teacher data (such as their targeted learning activities and their teaching goals). However, this would have been helpful to better understand the relations of the different technology-supported learning activities and learning outcomes. Therefore, future studies should aim for a larger sample size, especially on the course level.

Second, our study is solely based on subjective data. In other words, we were not able to take the actual learning activities that students performed into account, but rather the degree to which they felt encouraged to perform those activities. This might explain the low ICC2s as students might have referred to different course situations when rating the learning activities. Therefore, future studies should develop methods to measure in-course learning activities, as well as students' learning outcomes in a more objective way, e.g., by using video data, time-referenced ratings and objective knowledge tests. Yet, especially video ratings always run the danger of being extremely time-consuming. Also, it should be noted

that developing reliable measures that are economical to use is a challenging task, especially for cross-domain skills (Graesser et al., 2018).

Nevertheless, the approach that we implemented in the present study to investigate technology-supported learning from a more learner- than a technology-centered perspective proved to be helpful to better understand technology-supported teaching and its effects on learning in the context of higher education. In addition, we made a first step replicating and complementing some of the main ICAP ideas (Chi & Wylie, 2014) on the basis of a rather economical item-based methodological approach. Consequently, the ICAP model and the methodological approach we used in this study might act as a valuable extension of the TPACK framework.

Overall, our study implies that digital technology indeed has a strong potential to support learning processes and outcomes of students in higher education. However, results indicate that this potential is only partly used in higher education courses, thus suggesting a further learner-centered development of higher education teachers' technology use in courses.

## References

- Angeli, C., & Valanides, N. (2009). Epistemological and methodological issues for the conceptualization, development, and assessment of ICT–TPCK: Advances in technological pedagogical content knowledge (TPCK). *Computers & Education*, 52(1), 154–168. <https://doi.org/10.1016/j.compedu.2008.07.006>
- Backfisch, I., Lachner, A., Hische, C., Loose, F., & Scheiter, K. (2020). Professional knowledge or motivation? Investigating the role of teachers' expertise on the quality of technology-enhanced lesson plans. *Learning and Instruction*, 66, Article 101300. <https://doi.org/10.1016/j.learninstruc.2019.101300>
- Boekaerts, M. (1999). Self-regulated learning: Where we are today. *International Journal of Educational Research*, 31 (6), 445–457. [https://doi.org/10.1016/S0883-0355\(99\)00014-2](https://doi.org/10.1016/S0883-0355(99)00014-2)

- Bond, M., Marín, V. I., Dolch, C., Bedenlier, S., & Zawacki-Richter, O. (2018). Digital transformation in German higher education: Student and teacher perceptions and usage of digital media. *International Journal of Educational Technology in Higher Education*, 15(48). <https://doi.org/10.1186/s41239-018-0130-1>
- Brantley-Dias, L., & Ertmer, P. A. (2013). Goldilocks and TPACK: Is the construct ‘just right?’. *Journal of Research on Technology in Education*, 46(2), 103-128. <https://doi.org/10.1080/15391523.2013.10782615>
- Brooks, D. C. (2016). *ECAR study of undergraduate students and information technology, 2016. Research report*. ECAR.
- Brooks, D. C., & Pomerantz, J. (2017). *ECAR study of undergraduate students and information technology, 2017. Research report*. ECAR.
- Chai, C. S., Koh, J. H. L., & Tsai, C.-C. (2013). A review of technological pedagogical content knowledge. *Educational Technology & Society* 16 (2), 31–51. <https://www.jstor.org/stable/jeductechsoci.16.2.3>
- Chai, C. S., Koh, J. H. L., & Tsai, C.-C. (2016). A review of the quantitative measures of technological pedagogical content knowledge (TPACK). In M. C. Herring, M. J. Koehler, & P. Mishra (Eds.), *Handbook of technological pedagogical content knowledge (TPACK) for educators* (2nd ed., pp. 87–106). Routledge.
- Chen, J., Wang, M., Kirschner, P. A., & Tsai, C.-C. (2018). The role of collaboration, computer use, learning environments, and supporting strategies in CSCL: A meta-analysis. *Review of Educational Research* 88 (6), 799–843. <https://doi.org/10.3102/0034654318791584>
- Chi, M. T. (2009). Active-constructive-interactive: A conceptual framework for differentiating learning activities. *Topics in Cognitive Science* 1 (1), 73–105. <https://doi.org/10.1111/j.1756-8765.2008.01005.x>
- Chi, M. T., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist* 49 (9), 219–243. <https://doi.org/10.1080/00461520.2014.965823>
- Chi, M. T. H., Adams, J., Bogusch, E. B., Bruchok, C., Kang, S., Lancaster, M., Levy, R., Li, N., McEldoon, K. L., Stump, G. S., Wylie, R., Xu, D., & Yaghmourian, D. L. (2018). Translating the ICAP theory of cognitive engagement into practice. *Cognitive Science*, 42(6), 1777–1832. <https://doi.org/10.1111/cogs.12626>

- Chien, Y.-T., Chang, Y.-H., & Chang, C.-Y. (2016). Do we click in the right way? A meta-analytic review of clicker-integrated instruction. *Educational Research Review* 17, 1–18. <https://doi/10.1016/j.edurev.2015.10.003>
- Clark, H. (1996). *Using language*. Cambridge, England: Cambridge University Press.
- Clark, D., Sampson, V., Stegmann, K., Marttunen, M., Kollar, I., Janssen, J., Erkens, G., Weinberger, A., Menekse, M., & Laurinen, L. (2010). Online learning environments, scientific argumentation, and 21st century skills. In B. Ertl (Ed.), *Advances in Social Networking and Online Communities. E-collaborative knowledge construction* (pp. 1–39). IGI Global. <https://doi.org/10.4018/978-1-61520-729-9.ch001>
- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences*. Lawrence Erlbaum Associates.
- Fabian, K., Claves, E., & Kelly, L. (2019). Putting design into practice: An investigation of TPACK scores of lecturers in a networked institution. *Research in Learning Technology*, 27. <https://doi.org/10.25304/rlt.v27.2296>
- Galanek, J. D., Gierdowski, D. C., & Brooks, D. C. (2018). *ECAR study of undergraduate students and information technology, 2018. Research report*. ECAR.
- Graesser, A. C., Foltz, P. W., Rosen, Y., Shaffer, D. W., Forsyth, C., & Germany, M. L. (2018). Challenges of assessing collaborative problem solving. In E. Care, P. Griffin, & M. Wilson (Eds.), *Assessment and teaching of 21st century skills*, (pp. 75–91.). Springer.
- Harris, J. B., Phillips, M., Koehler, M. J., & Rosenberg, J. M. (2017). TPCK/TPACK research and development: Past, present, and future directions. *Australasian Journal of Educational Technology*, 33(3). <https://doi.org/10.14742/ajet.3907>
- Henderson, J. B. (2019). Beyond “active learning”: How the ICAP framework permits more acute examination of the popular peer instruction pedagogy. *Harvard Educational Review*, 89(4), 611–634. <https://doi.org/10.17763/1943-5045-89.4.611>
- Herring, M. C., Meacham, S., & Mourlam, D. (2016). TPACK development in higher education. In M. C. Herring, M. J. Koehler, & P. Mishra (Eds.), *Handbook of technological pedagogical content knowledge (TPACK) for educators* (2nd ed., pp. 207–223). Routledge.

- Hmelo-Silver, C. E. (2004). Problem-based learning: What and how do students learn? *Educational Psychology Review* 16 (3), 235–266.  
<https://doi.org/10.1023/B:EDPR.0000034022.16470.f3>
- Hox, J. J., Moerbeek, M., & van de Schoot, R. (2010). *Multilevel analysis: Techniques and applications*. Routledge.
- Koehler, M. J., Mishra, P., Hershey, K., & Peruski, L. (2004). With a little help from your students: A new model for faculty development and online course design. *Journal of Technology and Teacher Education*, 12(1), 25–55.  
<https://www.learntechlib.org/primary/p/14636/>
- Koehler, M. J., & Mishra, P. (2005). What happens when teachers design educational technology? The development of technological pedagogical content knowledge. *Journal of Educational Computing Research*, 32(2), 131–152.  
<https://doi.org/10.2190/0EW7-01WB-BKHL-QDYV>
- Koehler, M. J., & Mishra, P. (2008). What is technological pedagogical content knowledge (TPACK)? In AACTE Committee on Innovation and Technology (Ed.), *Handbook of technological pedagogical content knowledge (TPACK) for educators* (pp. 3–29). Routledge.
- Koehler, M. J., Shin, T. S., & Mishra, P. (2012). How do we measure TPACK? Let me count the ways. In R. N. Ronau, C. R. Rakes, & M. Niess (Eds.), *Educational technology, teacher knowledge, and classroom impact: A research handbook on frameworks and approaches* (Vol. 9, pp. 16–31). IGI Global. <https://doi.org/10.4018/978-1-60960-750-0.ch002>
- Koh, J. H. L., Chai, C. S., & Lim, W. Y. (2017). Teacher professional development for TPACK-21CL: Effects on teacher ICT integration and student outcomes. *Journal of Educational Computing Research*, 55(2), 172–196.  
<https://doi.org/10.1177/0735633116656848>
- Krathwohl, D. R. (2002). A revision of Bloom's taxonomy: An overview. *Theory into Practice* 41 (4), 212–218. [https://doi.org/10.1207/s15430421tip4104\\_2](https://doi.org/10.1207/s15430421tip4104_2)

- Lachner, A., Backfisch, I., & Stürmer, K. (2019). A test-based approach of modeling and measuring technological pedagogical knowledge. *Computers & Education*, *142*, Article 103645. <https://doi.org/10.1016/j.compedu.2019.103645>
- Law, N., & Chow, A. (2008). teacher characteristics, contextual factors, and how these affect the pedagogical use of ICT. In N. Law, & T. Plomp (Eds.), *Pedagogy and ICT Use* (pp. 181–219). Springer.
- Leary, H. M. (2012). *Self-directed learning in problem-based learning versus traditional lecture-based learning: A meta-analysis* [Doctoral dissertation, Utah State University]. DigitalCommons@USU. <https://digitalcommons.usu.edu/cgi/viewcontent.cgi?article=2177&context=etd>.
- Lou, Y., Abrami, P. C., & d'Apollonia, S. (2001). Small group and individual learning with technology: A meta-analysis. *Review of Educational Research* *71* (3), 449–521. <https://doi.org/10.3102/00346543071003449>
- Lübeck, D. (2009). *Lehransätze in der Hochschullehre* [Teaching approaches in higher education] [Doctoral dissertation, Freie Universität Berlin, Berlin, Germany]. Refubium. [https://refubium.fu-berlin.de/bitstream/handle/fub188/3534/01\\_Dissertationsschrift\\_DietrunLuebeck.pdf](https://refubium.fu-berlin.de/bitstream/handle/fub188/3534/01_Dissertationsschrift_DietrunLuebeck.pdf)
- Marcelo, C., Yot, C., & Mayor, C. (2015). University teaching with digital technologies. *Comunicar*, *23*(45), 117–124.
- Menekse, M., Stump, G. S., Krause, S., & Chi, M. T. (2013). Differentiated overt learning activities for effective instruction in engineering classrooms. *Journal of Engineering Education* *102* (3), 346–374. <https://doi.org/10.1002/jee.20021>
- Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record* *108* (6), 1017–1054. <https://doi.org/10.1111/j.1467-9620.2006.00684.x>
- Mourlam, D. (2017). Preparing for infusion: Emergence of a model for faculty TPACK development. *Journal of Technology and Teacher Education*, *25*(3), 301–325.
- Muthén, B. O., & Satorra, A. (1995). Complex sample data in structural equation modeling. *Sociological Methodology* *25*, 267–316. <https://doi.org/10.2307/271070>
- Muthén, L. K., & Muthén, B. O. (2017). Mplus (version 8) [Computer Software]. Los Angeles, CA, United States: Muthén & Muthén.

- Newman, T., & Beetham, H. (2017). *Student digital experience tracker 2017: The voice of 22,000 UK learners*. Jisc.  
<http://repository.jisc.ac.uk/6662/1/Jiscdigitalstudenttracker2017.pdf>
- Newman, T., Beetham, H., & Knight, S. (2018). *Digital experience insights survey 2018: Findings from students in UK further and higher education*. Jisc.  
[http://repository.jisc.ac.uk/6967/1/Digital\\_experience\\_insights\\_survey\\_2018.pdf](http://repository.jisc.ac.uk/6967/1/Digital_experience_insights_survey_2018.pdf)
- O’Conaill, B., & Whittaker, S. (1997). Characterizing, predicting, and measuring video-mediated communication: A conversational approach. In K. E. Finn, A. J. Sellen, and S. B. Wilbur (Eds.), *Videomediated communication*, (pp. 107–132). Lawrence Erlbaum Associates.
- Olofson, M. W., Swallow, M. J. C., & Neumann, M. D. (2016). TPACKing: A constructivist framing of TPACK to analyze teachers' construction of knowledge. *Computers & Education*, 95, 188–201. <https://doi.org/10.1016/j.compedu.2015.12.010>
- Partnership for 21st Century Learning (2015). *P21 framework definitions*.  
[http://static.battelleforkids.org/documents/p21/P21\\_Framework\\_Definitions\\_New\\_Logo\\_2015\\_9pgs.pdf](http://static.battelleforkids.org/documents/p21/P21_Framework_Definitions_New_Logo_2015_9pgs.pdf)
- Partnership for 21st Century Learning (2019). *Framework for 21st century learning: A unified vision for learning to ensure student success in a world where change is constant and learning never stops*.  
[http://static.battelleforkids.org/documents/p21/P21\\_Framework\\_Brief.pdf](http://static.battelleforkids.org/documents/p21/P21_Framework_Brief.pdf)
- Peugh, J. L., & Enders, C. K. (2004). Missing data in educational research: A review of reporting practices and suggestions for improvement. *Review of Educational Research* 74 (4), 525–556. <https://doi.org/10.3102/00346543074004525>
- Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, and M. Zeidner (Eds.), *Handbook of self-regulation*, (pp. 451–502). Academic Press.
- Sailer, M., Schultz-Pernice, F., Chernikova, O., Sailer, M., & Fischer, F. (2018). *Digitale Bildung an bayerischen Hochschulen – Ausstattung, Strategie, Qualifizierung und Medieneinsatz* [Digital education at Bavarian higher education institutions – facilities, strategy, qualification and technology use]. vbw. <https://www.vbw-bayern.de/Redaktion/Frei-zugaengliche-Medien/Abteilungen->

GS/Bildung/2018/Downloads/FINAL\_Digitale\_Bildung\_an\_bayerischen\_Hochschule\_n\_2.pdf

- Schiefele, U., & Pekrun, R. (1996). Psychologische Modelle des fremdgesteuerten und selbstgesteuerten Lernens. [Psychological models of externally controlled and self-regulated learning] In E. Weinert (Ed.), *Psychologie des Lernens und der Instruktion*, 249–278. Hogrefe.
- Schmid, R. F., Bernard, R. M., Borokhovski, E., Tamim, R. M., Abrami, P. C., Surkes, M. A., Wade, C. A., & Woods, J. (2014). The effects of technology use in postsecondary education: A meta-analysis of classroom applications. *Computers & Education* 72, 271–291. <https://doi/10.1016/j.compedu.2013.11.002>
- Schmid, U., Goertz, L., Radomski, S., Thom, S., & Behrens, J. (2017). *Monitor Digitale Bildung: die Hochschulen im digitalen Zeitalter* [Monitor digital education: Universities in the digital age]. Bertelsmann Stiftung.
- Tamim, R. M., Bernard, R. M., Borokhovski, E., Abrami, P. C., & Schmid, R. F. (2011). What forty years of research says about the impact of technology on learning: A second-order meta-analysis and validation study. *Review of Educational Research* 81 (1), 4–28. <https://doi.org/10.3102/0034654310393361>
- Vogel, F., Wecker, C., Kollar, I., & Fischer, F. (2017). Socio-cognitive scaffolding with computer-supported collaboration scripts: A meta-analysis. *Educational Psychology Review* 29 (3), 477–511. <https://doi.org/10.1007/s10648-016-9361-7>
- Voogt, J., Fisser, P., Roblin, N. P., Tondeur, J., & van Braak, J. (2013). Technological pedagogical content knowledge – a review of the literature. *Journal of Computer Assisted Learning*, 29(2), 109–121. <https://doi.org/10.1111/j.1365-2729.2012.00487.x>
- Wang, X., Wen, M., & Rosé, C. P. (2016). Towards triggering higher-order thinking behaviors in MOOCs. In D. Gašević, G. Lynch, S. Dawson, H. Drachsler, & C. Penstein Rosé (Eds.), *LAK '16 conference proceedings: The sixth international conference on learning analytics & knowledge* (pp. 398–407). ACM Press. <https://doi.org/10.1145/2883851.2883964>
- Wecker, C., & Fischer, F. (2014). Where is the evidence? A meta-analysis on the role of argumentation for the acquisition of domain-specific knowledge in computer-supported collaborative learning. *Computers & Education* 75, 218–228. <https://doi.org/10.1016/j.compedu.2014.02.016>

- Weinstein, C. E., Palmer, D. R., & Acee, T. W. (2016). *LASSI – user’s manual (3rd ed.)*. Clearwater, FL, United States: H & H.
- Willermark, S. (2018). Technological pedagogical and content knowledge: A review of empirical studies published from 2011 to 2016. *Journal of Educational Computing Research*, 56(3), 315–343. <https://doi.org/10.1177/0735633117713114>
- Wolters, C. A. (1998). Self-regulated learning and college students’ regulation of motivation. *Journal of Educational Psychology* 90 (2), 224–235. <https://doi.org/10.1037/0022-0663.90.2.224>
- Wu, Y.-T. (2013). Research trends in technological pedagogical content knowledge (TPACK) research: A review of empirical studies published in selected journals from 2002 to 2011. *British Journal of Educational Technology*, 44(3), E73-E76. <https://doi.org/10.1111/j.1467-8535.2012.01349.x>

## Tables and figures

Table 1. ICC1, ICC2 and design effects for learning activities and learning outcome.

	ICC1	ICC2	Design effect
Technology-support			
Passive	.07	.52	1.82
Active	.09	.46	2.05
Constructive	.04	.40	1.47
Interactive	.04	.41	1.47
Non-technology support			
Passive	<.01	<.01	1.00
Active	.05	.35	1.59
Constructive	<.01	.18	1.00
Interactive	.01	.22	1.12
Learning outcome			
Domain-specific knowledge	.11		2.29
Metacognitive strategies	.13		2.52
Motivational strategies	.09		2.05
Collaboration strategies	.13		2.52

*Note.*  $N = 381$ . Presented is the reliability of the proportions of variance at level-2 (ICC1), the reliability of the aggregated group-means (ICC2), and the ratio of the variance of the parameter in a given sample and the variance of the parameter in a random sample (Design effect).

Table 2. Descriptives and manifest correlations of technology-supported and non-technology-supported learning activities and learning outcomes.

	<i>M</i>	<i>SD</i>	Min	Max	Skew	Cronbach's $\alpha$	1	2	3	4	5	6	7	8	9	10	11
Technology support																	
1. Passive	3.86	0.80	1.00	5.00	-0.72	.65											
2. Active	3.00	0.83	1.00	5.00	-0.28	.65	.47**										
3. Constructive	3.37	0.73	1.00	5.00	-0.49	.76	.53**	.59**									
4. Interactive	3.11	0.89	1.00	5.00	-0.35	.80	.34**	.47**	.68**								
Non-technology support																	
5. Passive	2.77	0.90	1.00	5.00	-0.06	.60	.16**	.31**	.13*	.15**							
6. Active	2.78	0.89	1.00	4.75	-0.25	.72	.10	.43**	.18**	.16**	.66**						
7. Constructive	3.03	0.84	1.00	5.00	-0.35	.83	.11*	.29**	.27**	.28**	.63**	.67**					
8. Interactive	3.12	0.94	1.00	5.00	-0.23	.85	.08	.26**	.21**	.39**	.46**	.51**	.77**				
Learning outcome																	
9. Domain specific knowledge	3.33	0.75	1.00	5.00	-0.55	.80	.30**	.41**	.50**	.45**	.24**	.28**	.39**	.39**			
10. Metacognitive strategies	3.00	0.89	1.00	5.00	-0.25	.88	.24**	.49**	.48**	.49**	.28**	.36**	.38**	.38**	.82**		
11. Motivational strategies	2.98	0.85	1.00	5.00	-0.30	.81	.22**	.45**	.46**	.43**	.27**	.32**	.37**	.33**	.79**	.86**	
12. Collaboration strategies	3.29	0.86	1.00	5.00	-0.44	.83	.22**	.36**	.42**	.46**	.21**	.22**	.35**	.38**	.68**	.75**	.73**

Note.  $N = 381$ . \*  $p < .05$ ; \*\*  $p < .01$ .

Table 3. Standardized relations of (non-)technology-supported learning activities and learning outcomes.

	Learning outcomes			
	Domain-specific knowledge	Metacognitive strategies	Motivational strategies	Collaboration strategies
Technology-supported learning activities				
Passive	.01 [-.10; .13]	-.07 [-.16; .03]	-.08 [-.17; .01]	-.01 [-.13; .11]
Active	.15* [.04; .26]	.30** [.18; .41]	.26** [.14; .38]	.14* [.02; .25]
Constructive	.27** [.12; .42]	.16* [.00; .31]	.22* [.09; .35]	.15* [.01; .28]
Interactive	.18** [.06; .31]	.26** [.12; .40]	.19** [.07; .31]	.30** [.16; .43]
<i>R</i> <sup>2</sup>	.28** [.18; .38]	.33** [.23; .43]	.28** [.20; .36]	.24** [.16; .33]
Non-technology-supported learning activities				
Passive	-.02 [-.13; .09]	-.02 [-.12; .08]	.00 [-.11; .11]	-.01 [-.01; .13]
Active	.05 [-.11; .20]	.19* [.05; .34]	.12 [-.02; .26]	-.02 [-.17; .13]
Constructive	.23* [.05; .41]	.12* [-.03; .27]	.24** [.10; .38]	.16 [.033; .30]
Interactive	.22** [.06; .37]	.20** [.06; .34]	.09 [-.02; .19]	.26** [.15; .37]
<i>R</i> <sup>2</sup>	.19** [.11; .27]	.19** [.10; .28]	.16** [.08; .26]	.15** [.09; .22]

*Note.* *N* = 381. Presented are the standardized results of eight two-level regression models with each a technology-supported and non-

technology-supported learning activity as predictor and all learning outcomes as outcome variables. Coefficients with 95%- confidence intervals in square brackets. \**p* < .05; \*\**p* < .01.

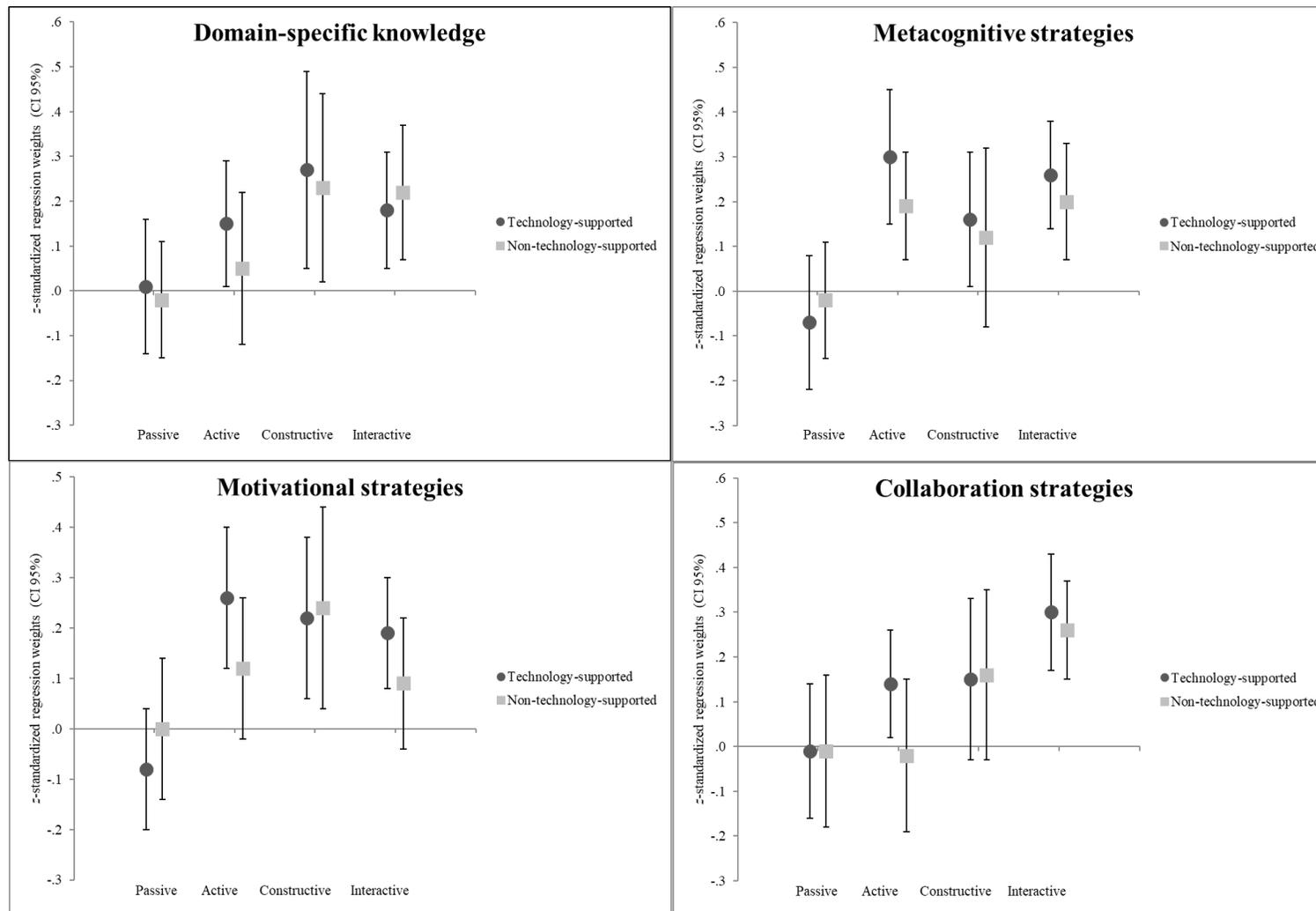


Figure 1. Z-standardized regression weights and 95%-confidence intervals of technology-supported and non-technology-supported learning activities for domain-specific knowledge, metacognitive strategies, motivational strategies, and collaboration strategies.