



Teaching with and teaching about technology – Evidence for professional development of in-service teachers

Josef Guggemos^{*}, Sabine Seufert

School of Management, Institute of Business Education and Educational Management, University of St.Gallen, St. Jakob-Strasse 21, 9000, St. Gallen, Switzerland

ARTICLE INFO

Keywords:

Digital transformation
Teacher professional development
TPACK
Will, Skill, Tool model
Teacher collaboration
DigComp framework

ABSTRACT

The digital transformation has implications for how and what to teach. For the purpose of professional development, the paper at hand presents a conceptual framework for predicting the use of technology as a means and as a content of instruction. It is informed by the TPACK framework and the ‘will, skill, tool’ model. The predictors are Technological Knowledge (TK), Technological Pedagogical Knowledge (TPK), Technological Pedagogical Content Knowledge (TPACK), Technological Collaboration Knowledge (TCoK), and Attitudes. These constructs are measured by newly developed self-assessment instruments. Structural equation modeling using a sample of 212 in-service teachers from commercial schools in German-speaking Switzerland lend support to the soundness of the measurement instrument and the conceptual framework. Overall, 36% of the variance of the use of technology as a means and 45% of the variance for the use as the content of instruction can be explained. Mediation and multigroup analyses, a finite-mixture segmentation, comparisons of competing models, and factor score regression yielded evidence for the robustness of the conceptual framework.

1. Introduction

Consensus may be that teachers play a crucial role in the process of integrating technology into instruction (Dillenbourg, 2013; Kirschner, 2015; Lawless & Pellegrino, 2007; OECD, 2015). Besides this, they might also be required to foster technology-related skills among students (Claro et al., 2018; Redecker, 2017; Siddiq, Scherer, & Tondeur, 2016). The 2018 Information and Computer Literacy Study (ICILS) summarizes this dual role as “Teaching with and about information and communications technologies” (Fraillon, Ainley, Schulz, Friedman, & Duckworth, 2019, p. 175). In the German-speaking context, this two-sidedness is represented in the construct (digital) media competencies that comprises media didactics and media education (Tiede, Grafe, & Hobbs, 2015). On the one hand, teachers are supposed to use technology in their instruction in a way that is conducive to achieving meaningful pedagogical goals; on the other, teachers may be supposed to integrate new content into their instruction or change the instructional focus due to the digital transformation. Information and communication technology (ICT) literacy, for instance, may become increasingly important for participating in society and for being successful in the workplace (Fraillon et al., 2019). Instruction in this regard may be necessary because students are not by nature proficient ICT users. The idea of

digital natives who use technology competently without specific training seems to be a myth (Kirschner & Bruyckere, 2017).

Teachers’ professional knowledge may become the focus point because it has been shown to be an important predictor for instructional quality (Baumert et al., 2010). Generic frameworks that address necessary knowledge in the context of digital transformation are available (Oberländer, Beinicke, & Bipp, 2020; Van Laar, van Deursen, van Dijk, & Haan, 2017). In Europe, the DigComp framework, issued by the European Commission, may be influential (Carretero, Vuorikari, & Punie, 2017). It comprises five facets: information and data literacy, digital collaboration and communication, digital content creation, ensuring digital safety, and solving technical problems. Based on the generic DigComp, the DigCompEdu framework adds further facets necessary for educators (Redecker, 2017). The DigCompOrg framework complements DigComp by addressing the integration of digital learning on an organizational level (Kampylis, Punie, & Devine, 2015). In the research-oriented literature, the TPACK framework (Koehler & Mishra, 2009; Mishra & Koehler, 2006), in particular, has gained broad attention (Petko, 2020; Voogt, Fisser, Pareja Roblin, Tondeur, & van Braak, 2013). Drawing from Shulman (1986, 1987), Mishra and Koehler (2006) added a further facet to content knowledge (CK) and pedagogical knowledge (PK): technological knowledge (TK). For the successful integration of

^{*} Corresponding author.

E-mail address: josef.guggemos@unisg.ch (J. Guggemos).

technology into a specific subject, TPACK, a combination of CK, PK, and TK, is necessary (Koehler & Mishra, 2009). Although widespread, the TPACK framework has been challenged (Angeli & Valanides, 2009). Graham (2011) argued that the delineation between the three elements is sometimes fuzzy, their relationship with each other needs clarification, and its use for predicting meaningful outcomes is doubtful. Moreover, TPACK addresses the integration of technology into instruction. Whether it could also contribute to the understanding of integrating technology-related content into instruction seems to be an open question. Research on teachers' professional knowledge about teaching technology-related content, in general, does not refer to the TPACK framework, but introduces new constructs. Examples are "Teachers' emphasis on developing students' digital information and communication skills" (Siddiq et al., 2016) and "Teaching in a Digital Environment Capacity" (Claro et al., 2018). In terms of theory building, it may be promising to investigate how these currently separated streams of research may inform each other in order to develop a parsimonious framework that covers both how to teach and what to teach in the context of digital transformation. In this vein, Graham (2011) pointed to an important aspect: the value of such a framework depends on its ability to predict meaningful outcomes. In the end, the desired outcome would be gains in student learning. However, the effects of the professional knowledge of an individual teacher on student learning may be hard to evaluate due to many confounding variables (Darling-Hammond, Newton, & Wei, 2010). Following the theory of planned behavior and technology acceptance models (Ajzen, 1991; Davis, 1989; Venkatesh, Thong, & Xu, 2012), a meaningful proximal outcome could be the intention to use or the actual use. These models imply that beyond professional knowledge further predictors may be considered. Following Teo and van Schaik (2012) and Scherer, Siddiq, and Tondeur (2019), attitudes, in particular, play an important role in predicting teachers' use of technology.

The aim of the study at hand is to develop and to validate a framework of in-service teachers' technology-related knowledge and attitudes in order to predict the use of technology as a means of instruction and as a content of instruction (Use). The purpose of this prediction is to obtain a better understanding for the professional development of teachers' technology-related knowledge and attitudes. Hence, we do not consider factors beyond the control of teachers, such as school characteristics, e.g., school equipment. This may be an issue because school equipment and resources, e.g., digital devices and high-speed internet, seem to play an important role for Use (European Commission, 2019; Fraillon et al., 2019; in contrast Gil-Flores, Rodríguez-Santero, & Torres-Gordillo, 2017). Since we do not consider school level variables (e.g., school equipment), although they might be important for Use, we will come back to this point in the method section. Overall, our research questions are:

RQ1. What technology-related knowledge and attitudes predict in-service teachers' use of technology as a means of instruction?

RQ2. What technology-related knowledge and attitudes predict in-service teachers' use of technology-related content in instruction?

In answering the two research questions, we aim at combining the two streams (how and what to teach) in order to identify technology-related professional knowledge and attitudes that are necessary for teaching with and about technology. By doing so, we could inform professional development programs of in-service teachers that aim at fostering technology-related knowledge and attitudes.

2. Theoretical framework

Adopting technology for learning purposes is a complex endeavor (Straub, 2009). Two kinds of models may be suitable for explaining teachers' use of technology: (1) technology acceptance models, and (2) the will, skill, tool (WST) model (Christensen & Knezek, 2008).

(1) With respect to teachers' acceptance and use of technology, Scherer, Siddiq, and Tondeur (2020) carried out a meta-analytical structural equation modeling study. They found that technology acceptance may only directly predict the use of technology instead of being mediated by behavioral intention. Although technology acceptance models are developed for predicting the use of technology, the underlying concept may also be helpful for predicting the integration of technology-related content into instruction. Technology acceptance models draw from the theory of planned behavior, which aims at explaining behavior in general (Ajzen, 1991). In the context at hand, it would imply that attitudes, subjective norms, and perceived behavioral control predict the intention to use technology-related content in instruction. Following Scherer et al. (2020), they may directly predict the actual use instead of behavioral intention. (2) The WST model has successfully been used to predict teachers' technology use (Agyei & Voogt, 2011; Petko, 2012). 'Will' can be defined as "a positive attitude toward the use of technology in instruction", 'skill' as "the ability to use and experience technology", and 'tool' as "availability, accessibility and extent of use of technology" (Knezek & Christensen, 2016, p. 311). Since from a professional development perspective, the tool component of the WST model may be without the control of individual teachers, we do not consider it in our framework. This is also the case for the social norm component of the theory of planned behavior, i.e., attitudes and behavioral control remain as predictors. From the individual teachers' perspective, we hypothesize their will (attitudes) and skill (behavioral control) to predict Use. Due to the purpose of our research, we restrict ourselves to technology-related knowledge and attitudes, i.e., we do not consider pedagogical content knowledge of specific subjects.

Drawing from the theory of planned behavior, we define attitudes as "the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question" (Ajzen, 1991, p. 188) and hypothesize:

H1. Positive attitudes towards technology in instruction positively predict the use of technology in instruction.

H2. Positive attitudes towards technology as content positively predict the use of technology-related content.

Petko (2012) suggested utilizing the TPACK framework in order to specify the skill component of the WST model. When it comes to the use of technology as a means of instruction across subjects, technological pedagogical knowledge (TPK) is the pertinent construct (Zhang, Liu, & Cai, 2019). In comparison to TPACK, it addresses knowledge relevant for all kind of subjects. For instance, cognitive activation using technology may play an important role in all kind of subjects. However, its manifestation in specific subjects could vary. Koehler, Mishra, and Cain (2013, p. 16) define TPK as an "understanding of how teaching and learning can change when particular technologies are used in particular ways". To specify this construct, it may be helpful to utilize research about PK. Voss, Kunter, and Baumert (2011) identified 'teaching methods', 'students' heterogeneity', 'classroom assessment', and 'classroom management' as facets of PK. TPK could be conceptualized as knowledge about how technology facilitates or changes those facets, e.g., how classroom management works in a technology-rich environment. We hypothesize:

H3. TPK positively predicts the use of technology in instruction.

When teaching about technology using technology, technology is the content as well as the means of instruction. In a formal sense, the letter 'C' of TPACK could be replaced by 'T'. Teaching with technology about technology may be a special form of TPACK that Koehler et al. (2013, p. 16) define as "an understanding that emerges from interactions among content, pedagogy, and technology knowledge". We refer to the DigComp 2.1 framework (Carretero et al., 2017) to delineate the content (= technology). This is consistent with the DigCompEdu framework (Redecker, 2017). Relying on DigComp may have two advantages. First,

instructional content is normative in nature and usually codified in official curricula or standards. Referring to the framework of the European Union may be a common factor across (European) countries. Second, the DigComp framework is, as the current version 2.1 implies, dynamic. By referring to DigComp, our own framework is also dynamic and keeps track of technological developments. Concerning this specific TPACK, i.e., knowledge about teaching with technology about technology, we hypothesize:

H4. TPACK positively predicts the use of technology-related content.

TPK and TPACK are associated (Koehler et al., 2013), the latter referring to a specific subject; hence, cross-disciplinary TPK may be conducive to TPACK. A teacher who has more knowledge about instructing with technology across various subjects may also demonstrate increased knowledge about teaching a specific subject, e.g., technology-related content. Indeed, Koh, Chai, and Tsai (2013) as well as Schmid, Brianza, and Petko (2020) provided empirical evidence for a positive influence of TPK on TPACK. We hypothesize:

H5. TPK positively predicts TPACK.

As Koehler et al. (2013) posit, TK is hard to define and if referring to specific technology would quickly lead to an outdated definition. As outlined for H4, we rely on the five facets of the DigComp 2.1 framework to delineate ‘technology’, i.e., teachers are expected to show the same kind of knowledge that they are supposed to foster among their students. TK may be the prerequisite for all other technology-related professional knowledge (Schmidt et al., 2009). In order to judge how technology can support the pursuit of pedagogical goals (in a specific subject), TK is necessary. In our context, TK also represents CK. Hence, just like CK, in general, we expect TK to positively predict TPACK. Indeed, Koh et al. (2013) showed that TK positively predicts both TPK and TPACK. We hypothesize:

H6. TK positively predicts TPK.

H7. TK positively predicts TPACK.

Professional learning communities or communities of practice (teacher communities) play an important role in the professional development process of teachers (Borko, 2004; Prenger, Poortman, & Handelzalts, 2019; Vangrieken, Meredith, Packer, & Kyndt, 2017; Warwas & Helm, 2018). This may also be the case in the realm of technology integration (Lawless & Pellegrino, 2007; Tseng & Kuo, 2014; Zhang et al., 2019). The activities of teacher communities may include the development of school curricula (Supovitz, 2002) or knowledge exchange (Vangrieken et al., 2017). Vangrieken, Dochy, Raes, and Kyndt (2015) summarize such activities as teacher collaboration. Tondeur, van Braak, Siddiq, and Scherer (2016) integrate ‘collaboration’ into their model for the preparation process of pre-service teachers for using technology in instruction. Agyei and Voogt (2012) report a positive influence of collaboration on the development of various facets of the TPACK framework among pre-service teachers. From a professional development perspective, the necessary knowledge to participate in such teacher communities may be put into focus. Since the study at hand restricts itself to technology, our construct Technological Collaboration Knowledge (TCoK) addresses teachers’ knowledge about how to use technology in order to collaborate with other teachers, e.g., using databases to exchange knowledge. Drawing from the theory of planned behavior, such knowledge may be an important (indirect) predictor for actual collaboration: Teachers with higher TCoK may collaborate more in terms of quality and quantity, which positively predicts TPK and TPACK. We hypothesize:

H8. TCoK positively predicts TPK.

H9. TCoK positively predicts TPACK.

Since TCoK has, as the name implies, a technology component, we expect TK to be conducive for TCoK. Teachers who have general

knowledge about digital content creation and collaboration using technology may also be able to use this general knowledge to collaborate with their colleagues. We hypothesize:

H10. TK positively predicts TCoK.

Fig. 1 summarizes our conceptual framework.

3. Method

3.1. Instruments

The validity of a measurement depends on its intended use (AERA, APA, & NCME, 2014). Self-assessment instruments may be suitable from a professional development perspective. As the theory of planned behavior implies, self-perceptions (indirectly) predict behavior. Self-assessment instruments tend to capture self-efficacy, which could be a good predictor for teachers’ use of technology (Scherer, Tondeur, & Siddiq, 2017; Voogt et al., 2013). Moreover, self-assessment instruments are well established in research about technology acceptance (Nistor, 2014), the WST model (Knezek & Christensen, 2016; Petko, 2012), and TPACK (Scherer et al., 2017; Schmid et al., 2020; Valtonen et al., 2017). Against this backdrop, we utilize a self-assessment instrument to capture the constructs of our conceptual framework. The development of the instrument was informed by fourteen expert interviews. These experts show a diverse background: teachers, school principals, educational policy makers, federation representatives, and researchers in the realm of digital transformation. A first draft of the instrument was pretested with a sample of 132 teachers and, based on this, refined. By means of focus group discussions with the school management teams at five partner schools, we compiled the final instrument (Seufert, Guggemos, Tarantini, & Schumann, 2019). For the purpose of this study, we reduced the complexity of the DigComp 2.1 related measurement instruments, namely TK and TPACK. In the original version they have a higher-order structure where the five facets of the DigComp 2.1 framework are captured with several items and these five facets operationalize TK and TPACK. For the purpose of parsimony, we measure TK and TPACK with five items corresponding to the five facets of the DigComp 2.1 framework. Convergent validity may be achieved because the latent correlation of the constructs measured with the full instruments and the reduced ones utilized in the present study are greater than 0.912. All the used items in this study can be found in S1 in the Appendix. The knowledge and attitude constructs are captured using a seven-point scale of rating ranging from “does not apply at all” to “applies very strongly”. A five-point scale of rating is utilized to measure the items for Use: never, infrequently (1–2 times per semester), occasionally (3–5 times per semester), frequently (every month), and very frequently (every week).

3.2. Data collection and sample

Our sample comprises 212 in-service teachers at commercial vocational schools in German-speaking Switzerland. To obtain the sample, we contacted all commercial vocational schools in German-speaking Switzerland. Besides the five partner schools, which were involved in the development of the instrument, four further schools participated. An online questionnaire was given to all teachers at the nine schools. Participation was voluntary and anonymous. We checked for potential outliers by means of univariate (boxplots) and multivariate (Mahalanobis distances) methods. We inspected all of the potential five outliers and decided not to exclude any observations. Table 1 summarizes the key characteristics of our sample and any missing values in the context variables. For all other variables (see S1 in the Appendix), 3.2% of missing values occurred. Due to a non-significant Little’s MCAR test ($\chi^2(1612) = 1834.321, p = 1$) and having inspected the missing data patterns, we treat them as missing completely at random.

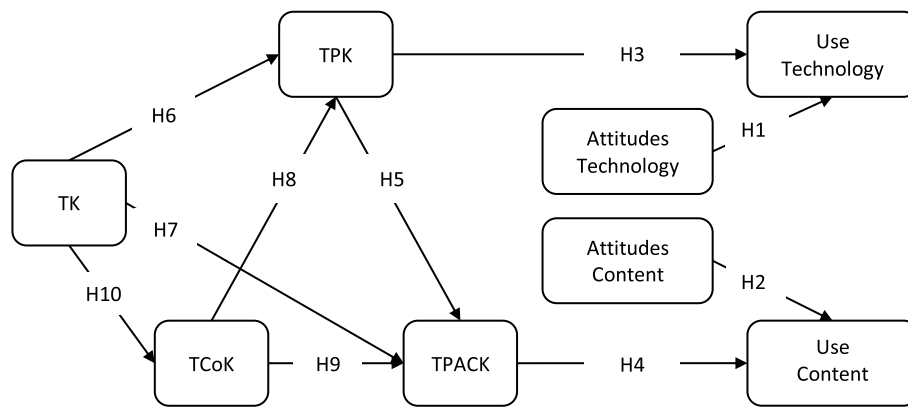


Fig. 1. Conceptual framework for predicting use of technology as a means of instruction and use of technology as a content of instruction with teachers’ professional knowledge and attitudes.

Table 1
Characteristics of the sample (N = 212).

Variable	Manifestation	Frequency	Percent
Gender	Female	105	49.5
	Male	105	49.5
	Missing	2	1.0
Age [years]	<36	22	10.4
	36–45	47	22.2
	46–55	87	41.0
	56–65	56	26.4
	Missing	0	0.0
Teaching experience [years]	1–5	25	11.8
	6–10	36	17.0
	11–15	36	17.0
	16–20	35	16.5
	>20	77	36.3
	Missing	3	1.4

3.3. Data analysis

First, we group mean center the covariates to control for heterogeneity between the nine schools in our sample (Bell, Jones, & Fairbrother, 2018). Teachers’ professional knowledge and attitudes are contrasted with the knowledge and attitudes of other teachers from the same school (group mean), instead of from the entire sample (grand mean). By removing the between-school variance, the estimated coefficients only represent individual level effects. This tackles the issue that we do not consider the tool component of the WST model; the reported associations are not influenced by varying equipment, resources, and support across the nine schools.

Since we aim at testing the structure of our conceptual framework, we rely on covariance-based structural equation modeling (CB-SEM) (Hair, Risher, Sarstedt, & Ringle, 2019). Our data, measured, at the least, on five-point scales of rating, show slight deviations from a normal distribution. Moreover, teachers are nested in nine schools. Hence, we utilize a maximum likelihood estimator (MLR) that is robust against slight deviations from a normal distribution and non-independence of observations (cluster robust standard errors). In light of this, we report χ^2 statistics after considering the Satorra Bentler correction: $SB-\chi^2$ (Satorra & Bentler, 2010). Due to our assumption of data missing completely at random, we rely on full information maximum likelihood to handle the missing data (Jia & Wu, 2019). We use the R-package lavaan 0.6–5 for all CB-SEM based analyses (Rossee, 2012).

For assessing the quality of our measurement instrument, Cronbach’s α and McDonalds’ ω act as measures for reliability (Scherer et al., 2017). A cut-off value for an acceptable reliability could be 0.7 (Hair et al., 2019). Convergent validity of the measures may be ensured if the average variance extracted (AVE) is larger than 0.5; discriminant

validity if the heterotrait–monotrait (HTMT) ratio is smaller than 0.9 for conceptual similar constructs (Hair et al., 2019). The HTMT ratio is defined as the mean value of the item correlations across constructs relative to the geometric mean of the average correlations for the items measuring each construct. The HTMT ratio has been demonstrated to be superior to the Fornell-Larcker criterion for detecting lack of discriminant validity (Franke & Sarstedt, 2019). A rigorous assessment of discriminant validity may be important because Scherer et al. (2017) showed substantial similarity between the facets of the TPACK framework. To assess the overall model fit of the framework, we use CFI and TLI as comparative measures, and RMSEA and SRMR as absolute ones. The following values serve as cut-off values (Van de Schoot, Lugtig, & Hox, 2012): acceptable fit: CFI and TLI > 0.90, RMSEA < 0.08, SRMR < 0.10; good fit: CFI and TLI > 0.95, RMSEA < 0.05, SRMR < 0.06. In case of an acceptable model fit, we modify our measurement model (Schmid et al., 2020) in order to achieve a good fit.

As can be seen from Fig. 1, our conceptual framework contains indirect paths that imply mediation, e.g., from TK via TPK to Use Technology. For the theoretical soundness of the conceptual framework, it is important to evaluate the kind of mediation involved. To this end, we rely on Zhao, Lynch, and Chen (2010) who revised the approach of Baron and Kenny (1986). Following Zhao et al. (2010), an indirect-only mediation could indicate that the mediators in the model are consistent with the theoretical framework. It is characterized by a significant indirect path and, at the same time, non-significant direct path. In our case, for instance, this would imply that the indirect path from TK to Use Technology is significant, but a direct path from TK to Use Technology is not significant. If the direct path was also significant, this would point to an incomplete theoretical framework: there may be further not-yet-considered mediators hidden in the ‘direct’ path. To assess the statistical significance of the indirect paths, we use bias-corrected bootstrapping with 5000 samples to create the 95% confidence intervals (Preacher & Hayes, 2008). If the 95% confidence interval does not include zero, the indirect path is regarded as significant.

Observed and unobserved heterogeneity may influence the reported path coefficients. In terms of observed heterogeneity, moderators could be teachers’ gender, age, and main subject (Siddiq et al., 2016). Due to convergence problems, we cannot rely on CB-SEM to check for moderators by means of multigroup analyses. The reason is the relatively small sample size in our study. As an alternative, we rely on partial least squares SEM (PLS-SEM) that has, in comparison to CB-SEM, smaller formal sample size requirements (Hair et al., 2019). In the case of our conceptual framework, fifty teachers in each group could be sufficient. Before carrying out multigroup analyses, we check for measurement invariance by means of permutation tests (Henseler, Ringle, & Sarstedt, 2016). In terms of age, we form three groups: under 46 years (junior, n = 69), 46–55 years (middle, n = 87), and 56+ years (senior, n = 56).

Concerning the main subject, there are only two groups with a sufficient sample size: business education (n = 70) and language teachers (n = 66). Finally, we use PLS-SEM to control for unobserved heterogeneity by means of a finite mixture segmentation. Evidence for the absence of unobserved heterogeneity may be a lower information criterion AIC3 and CAIC for a one-class model in comparison to every multiclass solution (Sarstedt, Becker, Ringle, & Schwaiger, 2011). We utilize SMART-PLS 3.3.2 for all PLS-SEM related analyses.

4. Results

All response patterns to the items (see S1 in the Appendix) show significant deviations from a normal distribution (Shapiro Wilk test: $p < .05$). However, the deviations are not severe. The absolute values for skewness and kurtosis are below 1.14 and 4.99, respectively. The teachers in the sample show an overall positive attitude toward technology as a means of instruction and technology-related content, which is indicated by a mean on the seven-point scale of rating of 5.45 and 4.99, respectively. A mean of 2.308 and 2.357 on a five-point scale of rating for Use Technology and Use Content, respectively, points to an infrequent to occasional use.

The quality of the measurement model is decent (see Table 2). Cronbach’s α and McDonald’s ω is greater than 0.7 for all constructs. The AVE is greater than 0.5 with one exception. For TK it equals 0.475, which is only slightly below the cut-off value of 0.5. The reason is item 12 (see S1 in the Appendix) that shows a factor loading of 0.59. Overall, however, convergent validity may be achieved. Discriminant validity might also be ensured. The highest HTMT ratio appears for TPK and TPACK with 0.813. This is well below the cut-off value of 0.9. Even the 95% confidence interval of this HTMT ratio is below 0.90 [0.730, 0.881].

The initial structural equation model shows an acceptable fit $SB-\chi^2(362) = 565.229$ ($p < .001$), CFI = 0.942, TLI = 0.935, RMSEA = 0.051 (90% CI = [0.044, 0.059]), SRMR = 0.060. By including four residual correlations between items, we obtained a good fit. Fig. 2 shows these residual correlations and the fit values of the adjusted model. The considered residual correlations may be reasonable from a conceptual point of view. For instance, TK items 12 and 13 (see S1 in the Appendix) address rather technical aspects whereas the other TK items cover conceptual aspects like information literacy and communication. However, there are no differences between the initial structural model and the adjusted model (with residual correlations) in terms of sign and statistical significance. All hypothesized paths are significant at the 5% level. The evidence reported throughout this paper is based on the adjusted model.

As Table 3 shows, all the indirect paths in our conceptual framework are statistically significant. To assess the type of mediation, we inserted (at once) potential direct paths. However, they are all non-significant: TK → Use Technology ($-0.054, p = .828$), TK → Use Content ($-0.178, p = .268$), TCoK → Use Technology ($-0.062, p = .772$), TCoK → Use Content ($-0.020, p = .892$), TPK → Use Content ($-0.044, p =$

.804). These findings of significant indirect paths and, at the same time, non-significant direct paths point to indirect-only mediations.

In terms of the multilevel structure (teachers nested in nine schools), the intraclass correlation coefficient ICC(1) of the two outcome variables Use Technology and Use Content equals 0.149 and 0.001, respectively. For all other variables, the ICC(1) ranges between 0.004 (TK) and 0.065 (TPK). Although the between-school variance may not be small enough to be ignored, group mean centering does not have any influence on the signs of the path coefficients and their statistical significance at the 5% level. Consistent with the substantial between school variance for Use Technology, the explained variance drops from 45.9% to 36.0% when using group mean centered predictors instead of predictors derived from the raw data.

The PLS-SEM measurement model and structural model showed good properties (Hair et al., 2019). Moreover, PLS-SEM yielded the same results as CB-SEM in terms of sign and significance at the 5% level. The results of the PLS-SEM multigroup analyses are depicted in Table 4. There are differences in path coefficients for all three hypothesized moderators. Worth noting, although there are no differences in path coefficients, compositional measurement invariance seems to be an issue between junior teachers, on the one hand, and middle as well as senior teachers, on the other. The problematic items are 15 (junior vs. senior), and 17 and 18 (junior vs. middle), see S1 in the Appendix for items. All these items pertain to TPK.

Concerning unobserved heterogeneity, the finite mixture segmentation indicated a one-class solution as the best trade-off between model complexity and parsimony: one class: AIC3 = 2,509, CAIC = 2,559; two classes: AIC3 = 2,519, CAIC = 2,623; three classes: AIC3 = 2,532, CAIC = 2,690. All models with more than three classes also show worse AIC3 and CAIC in comparison to the one-class solution.

Since our conceptual framework (see Fig. 1) is not the only possible one, we compared it with competing models by including reasonable further paths. TCoK could positively predict TK. Moreover, TPK and TPACK might predict TCoK. Besides this, it is an open question if the specific TPACK that refers to the instruction of technology related content could also positively predict Use Technology that addresses teaching with technology across subjects (Petko, 2020). Moreover, TPK might directly predict Use Content besides the already considered path via TPACK. However, none of these paths is statistically significant at the 5% level: TCoK → TK (0.207, $p = .443$), TPK → TCoK (0.187, $p = .293$), TPACK → TCoK (0.152, $p = .484$), TPK → Use Content ($-0.046, p = .706$), TPACK → Use Technology ($-0.012, p = .924$).

5. Discussion and limitations

The aim of our research was to predict teachers’ use of technology as a means of instruction (RQ1) and the use of technology-related content in instruction (RQ2) for the purpose of professional development. The findings lend support to our conceptual framework, depicted in Fig. 1, because all hypotheses were accepted. Moreover, CB-SEM and PLS-SEM

Table 2 Descriptives for constructs, assessment of measurement model, and latent correlations among constructs (N = 212).

-	Construct	α	ω	AVE	HTMT	Latent correlation among constructs								
						1	2	3	4	5	6	7	8	
1	Attitudes Technology	.883	.897	.804	<.698	1.00								
2	Attitudes Content	.924	.925	.861	<.698	.669	1.00							
3	TCoK	.874	.904	.664	<.685	.541	.516	1.00						
4	TK	.853	.773	.475	<.722	.644	.639	.656	1.00					
5	TPK	.915	.916	.685	<.813	.598	.586	.627	.634	1.00				
6	TPACK	.903	.906	.652	<.813	.614	.650	.692	.692	.821	1.00			
7	Use Technology	.883	.891	.621	<.646	.523	.347	.357	.410	.571	.495	1.00		
8	Use Content	.805	.811	.592	<.670	.481	.507	.442	.442	.553	.669	.610	1.00	

Note. α = Cronbach’s α , ω = McDonald’s ω , AVE = Average variance extracted, HTMT = Heterotrait–monotrait ratio. All correlation significant at the 0.1% level (two-sided) considering the cluster structure of the data (teachers nested in nine schools). Constructs 1–6 are measured on a seven-point scale of rating, constructs 7 and 8 on a five-point scale of rating. Item loadings, means, and standard deviations are reported in S1 in the Appendix.

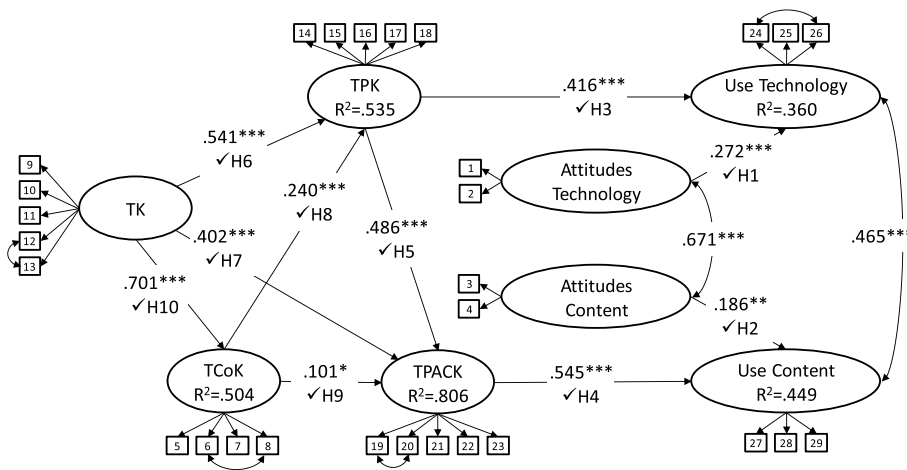


Fig. 2. Structural equation model to predict ‘Use Technology’ and ‘Use Content’ (N = 212). Note. Standardized path coefficients. Assessment of significance based on cluster robust standard errors (cluster = schools). *p < .05, **p < .01, ***p < .001. Fit values: SB- χ^2 (358) = 513.121 (p < .001), CFI = 0.956, TLI = 0.950, RMSEA = 0.048 (90% CI = [0.038, 0.057]), SRMR = 0.050. For reasons of clarity, the latent correlation between Attitudes Technology and Attitudes Content with TK is not depicted (0.699 and 0.705, p < .001). All factor loadings, see S1 in the Appendix, are significant (p < .001).

Table 3
Indirect paths of the conceptual framework (N = 212).

Outcome	Mediator(s)	Predictor	Specific indirect			Total indirect		
			Std. Coef.	Coef.	95% CI	Std. Coef.	Coef.	95% CI
Use Technology	TPK	TK	0.225	0.200	(0.081, 0.319)	0.296	0.263	(0.129, 0.396)
	TCoK, TPK		0.071	0.063	(0.033, 0.093)			
	TPK	TCoK	0.100	0.070	(0.003, 0.215)	0.100	0.070	(0.033, 0.107)
Use Content	TPACK	TK	0.219	0.177	(0.091, 0.263)	0.447	0.361	(0.283, 0.439)
	TCoK, TPK, TPACK		0.045	0.037	(0.012, 0.061)			
	TCoK, TPACK		0.039	0.032	(0.003, 0.060)			
	TPK, TPACK		0.144	0.116	(0.039, 0.193)			
	TPACK	TPK	0.265	0.196	(0.099, 0.292)			
	TPACK	TCoK	0.055	0.035	(0.001, 0.070)	0.119	0.076	(0.018, 0.134)
	TPK, TPACK		0.064	0.041	(0.009, 0.073)			

Note. Coef. = unstandardized path coefficients. Std. Coef. = standardized path coefficients. Confidence intervals based on bias corrected bootstrapping with 5000 samples.

Table 4
Multigroup analyses: Significant different path coefficients.

Moderator	Manifestation	Path	Std. Coef.	Dif.	p-value		
Gender	Male (n = 105)	TK → TCoK	0.408	0.265	.006		
	Female (n = 105)		0.673				
	Male (n = 105)	TPACK → Use Content	0.377			0.228	.043
	Female (n = 105)		0.605				
Age	middle (n = 87)	TK → TPACK	0.391	0.263	.025		
	senior (n = 56)		0.128				
	middle (n = 87)	TPK → TPACK	0.318			0.291	.027
	senior (n = 56)		0.609				
Main subject	Business (n = 70)	TCoK → TPK	0.134	0.445	.010		
	Language (n = 66)		0.578				
	Business (n = 70)	TK → TPK	0.569			0.516	.003
	Language (n = 66)		0.053				

Note. Std. Coef. = standardized path coefficients, Dif. = difference in path coefficients. P-values based on Bootstrapping (BCa) with 5000 samples. Compositional measurement invariance is ensured (Henseler et al., 2016).

yielded identical results in terms of sign and statistical significance at the 5% level. This multimethod approach provides evidence for the robustness of our findings (Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016). Furthermore, it may, indeed, be necessary to separate the

constructs Use Technology and Use Content. They can clearly be separated (HTMT ratio = 0.646) and their latent correlation of 0.465 is significantly below 1 (see Fig. 2). The correlations among TK, TPK, and TPACK found in our study are well in line with other studies based on

self-assessment instruments (Koh et al., 2013; Schmidt et al., 2009). For instance, the manifest correlation between TPK and TPACK equals .74, exactly the same value reported by Koh et al. (2013). In comparison to those studies, however, the correlation in our study is comparatively higher between TK and TPACK. This is in line with the conception that TK also represents CK when teaching with technology about technology. Overall, the measurement instrument shows decent reliability ($\alpha > 0.853$), convergent validity ($AVE > 0.475$), and discriminant validity ($HTMT \text{ ratio} < 0.813$). The overall fit of the model, when considering four residual correlations between items, is good: CFI = 0.956, TLI = 0.950, RMSEA = 0.048, SRMR = 0.050. To check for substantially relevant local model misspecifications, we also inspected the expected parameter change in combination with the modification index (Saris, Satorra, & van der Veld, 2009); however, we did not detect any signs of this. As Scherer et al. (2017) showed, it may be hard to separate the constructs of the TPACK framework. Our measurement instrument might ensure, at the very least, an acceptable separation of the constructs (discriminant validity). In terms of the quality of our prediction, we were able to explain 36.0% and 44.9% of the variance for Use Technology and Use Content, respectively. This is in line with Ageyi and Voogt (2011) who reported an R^2 when considering 'will' and 'skill' of 41%–42% (depending on the model) for integration of technology. Knezek and Christensen (2016) claim explained variances of >60% for the WST model. However, a fair comparison is not possible because in our research we only consider will and skill as we focused on the individual teacher's technology-related knowledge and attitudes.

To judge the theoretical soundness of our conceptual framework, it was important to determine the kind of mediation. Our findings of indirect-only mediations may be evidence for a correctly specified conceptual framework (Zhao et al., 2010). Namely, the direct paths from TK to Use are non-significant. It indicates that only TPK and TPACK directly predict Use. Moreover, TPK does not directly predict Use Content but the indirect path via TPACK is significant. This finding may indicate that considering the domain-specific TPACK in addition to the domain-independent TPK yields additional insights and should be retained. Furthermore, TCoK is not directly associated with Use. Rather, it predicts TPK and TPACK and, indirectly, Use. This is in line with the conceptualization of the construct as an important aspect in the professional development process of teachers in the context of digital transformation. Again, CB-SEM and PLS-SEM led to identical results for all these analyses.

The multigroup analyses in combination with measurement invariance analyses yielded some remarkable findings. First, the latter analyses indicated a substantially different understanding of TPK between junior teachers (<46 years old), on the one hand, and middle and senior teachers (46+ years old) on the other. This may not be surprising because pedagogical approaches and technology have substantially changed over time. Our findings may also caution against taking measurement invariance in terms of age for granted. Apart from age, we found evidence for compositional measurement invariance in terms of gender and main subject. This might point to a fairly similar understanding across gender and teachers with different main subjects. What is remarkable is the substantially higher association between TK and TPK for business education teachers in comparison to language teachers (0.569 vs. 0.053). Besides this, however, the path coefficients in the structural model are fairly similar. In summary, the main source of observable heterogeneity between teachers might be age. Teachers in the middle and senior group (46+ years old) seem to have a different understanding of TPK in comparison to teachers who are younger. These findings may be in line with the ICILS (Fraillon et al., 2019). Despite some differences in path coefficients, however, the result of a one-class solution in the finite mixture segmentation points to a one-class solution for the entire sample as a good trade-off between model complexity and parsimony. Overall, we regard our conceptual framework as robust against various forms of heterogeneity.

Our study has several limitations that have to be mentioned. Due to

cross-sectional data, we cannot make any causal claims. Longitudinal data would be more suitable to investigate the relationships between the constructs in our study, e.g., by using cross-lagged panel designs. Moreover, our sample is limited. It comprises only 212 in-service teachers from nine commercial vocational schools in German-speaking Switzerland who voluntarily participated in the study. At least the sample size may not be an issue. As a robustness check, we carried out factor score regression. In case of small samples sizes, using regression factor scores could yield higher precision in comparison to structural equation modeling (Loncke et al., 2018). To this end, we utilized the syntax provided by Loncke et al. (2018). The fit of the factor score model is good: $SB-\chi^2(14) = 19.235$ ($p = .156$), CFI = 0.995, TLI = 0.992, RMSEA = 0.043 (90% CI = [0.000, 0.087]), SRMR = 0.028. The path coefficient of the factor score regression and those of the structural equation model are identical in terms of sign and statistical significance at the 5% level. The second-level sample size of only nine schools prevented us from investigating school level relationships, i.e., to take the multilevel structure fully into account. Furthermore, we relied solely on teachers' self-reports, which may raise concerns about common methods bias (Conway & Lance, 2010). For Use, in particular, it would be beneficial to have objective measures. Moreover, it could be revealing to take, besides the quantity of Use, also its quality into account (Sailer et al., 2021; this issue). In this vein, however, it has to be stressed that any measurement can only be evaluated with respect to its purpose (AERA et al., 2014). We agree with Backfisch, Lachner, Hische, Loose, and Scheiter (2020) that the self-assessment instruments of TPK and TPACK have disadvantages. If the purpose is to capture professional knowledge in order to support professional development, however, it should be taken into account that performance tests in high-stakes contexts could have negative side effects, e.g., evoke negative emotions among teachers (Ryan & Weinstein, 2009).

Moreover, we did not consider the actual degree of collaboration among teacher. The direct association of TCoK and TPK as well as of TCoK and TPACK (see Fig. 1) is likely be mediated by the actual level of collaboration. In further studies, it may be revealing to include the level of technology-supported collaboration (quality and quantity) as a mediator.

6. Implications

6.1. Theoretical implications

The paper at hand contributes to the knowledge base about the TPACK framework in many ways. Graham (2011) pointed out three problems in TPACK research: 1) What, 2) How, and 3) Why. Our research also addresses all three areas.

1) What. The trade-off between comprehensiveness and parsimony guided the development of our conceptual framework for predicting the use of technology as a means and as a content of instruction. Currently, the two types of use are discussed separately. We argue that when teaching with technology about technology, technology also represents the content. The corresponding knowledge may be regarded as TPACK. Based on this assumption, it is not necessary to integrate a specific construct for teachers' knowledge on teaching with technology, about technology, into the conceptual framework. Moreover, this assumption reduces the complexity of the TPACK framework because CK and its interactions with other constructs, e.g., TCK, equal TK.

Since the publication of the well-established TPACK self-assessment instrument of Schmidt et al. (2009), research on teachers' professional knowledge has progressed. Hence, we took into account recent research about teachers' general pedagogical knowledge (Depaepe & König, 2018; Voss et al., 2011) and high-quality instructional settings (Praetorius, Pauli, Reusser, Rakoczy, & Klieme, 2014). Referring to research about PK could contribute to the theoretical founding of TPK and keep such knowledge up to date as regards the state of research about high-quality learning settings.

According to [Graham \(2011\)](#), as well as [Koehler and Mishra \(2009\)](#), it is especially difficult to capture the technology facet. We relied on the DigComp 2.1 framework ([Carretero et al., 2017](#)), which may have two advantages. DigComp 2.1 is, as the name implies, dynamic. Hence, new technological developments are automatically integrated into our conceptual framework too. Moreover, it contributes to the parsimony of our conceptual framework: the DigComp framework is used to delineate TPACK, as well as TK.

TPACK and TK are normative in nature. In our case, the DigComp framework determines what knowledge teachers are expected to foster among students (TPACK) and should possess themselves (TK). This is legitimate because we developed the conceptual framework in collaboration with the schools in our sample; the school management teams agree with the framework. However, researchers or practitioners who want to adapt our instrument have to examine whether the conception of TK and TPACK is in line with curricula or standards pertinent to them. Moreover, the instruction should also be considered ([Pellegrino, DiBello, & Goldman, 2016](#)), i.e., the measurement instrument should be consistent with the content that teachers are taught or are supposed to develop informally.

Although the importance of collaboration in the professional development of teachers is well documented, this aspect has rarely been explicitly considered in quantitative research about teachers' technology integration. The consideration of the construct TCoK in the conceptual framework was highly recommended by the school representatives involved in the development process ([Seufert, Guggemos, Tarantini, & Schumann, 2019](#)). From their point of view, professional development in the context of digital transformation requires joint effort and, thus, TCoK. Our findings lend support to this assertion as we show that at the individual teacher level, TCoK significantly predicts TPK and TPACK and, indirectly, Use. However, further research is necessary for a better understanding of the role of TCoK in the professional development process. The actual level of collaboration and its quality are likely to mediate the relationship between TCoK and TPK and TPACK. Moreover, in line with the theory of planned behavior, attitudes towards technology-related collaboration should be considered.

2) How. [Angeli and Valanides \(2009\)](#) criticized the unclear relationship among the constructs of the TPACK framework. [Koh et al. \(2013\)](#) posited a relationship among the constructs of the TPACK framework and provided evidence for their hypotheses. We were able to replicate the model structure of [Koh et al. \(2013\)](#). The added value of our work when compared to [Koh et al. \(2013\)](#) is the mediation analysis. As we showed, not all constructs, e.g., TK, directly predict Use.

Our findings may contribute to a better understanding of the relationships between the constructs of the TPACK framework from a prediction perspective. For a factor analytical perspective, see [Scherer et al. \(2017\)](#).

The delineation of the constructs in the TPACK framework is a regular problem. As we showed, our measurement model has sufficient discriminant validity (HTMT ratio < 0.813). Moreover, the overall model fit indices are good (CFI = 0.956, SRMR = 0.050). By developing a refined TPACK measurement instrument, we might have followed [Scherer et al. \(2017, p. 13\)](#) who "encourage the further development of TPACK measures that might distinguish more clearly between the different knowledge dimensions and further validation studies that investigate the substantial meaning of the specific TK factor".

3) Why. TPACK research rarely addresses the usefulness of this framework to predict meaningful outcomes. An exception for in-service teachers is [Hsu \(2016\)](#) who integrated the TPACK framework into a technology acceptance model to predict the adoption of mobile-assisted language learning. We combined the TPACK framework with the WST model to predict teachers' use of technology as a means of instruction and as a content of instruction. Both forms of use may be important in the context of digital transformation ([Fraillon et al., 2019](#)). In line with the WST model and the theory of planned behavior, our findings show that besides the TPACK constructs, attitudes should be considered for

predicting Use. Solely relying on the TPACK framework may not be sufficient if the aim is to predict Use ([Petko, 2012](#)). However, TPK and TPACK might be the most important predictors. In comparison to TPK and TPACK (skill), attitudes (will) show a lower predictive power. This is in line with [Agyei and Voogt \(2011\)](#) who reported skill as the most important predictor among pre- and in-service teachers. Interestingly, for pre-service teachers' technology integration, will seems to be a better predictor than skill ([Farjon, Smits, & Voogt, 2019](#)). Such differences between pre- and in-service teachers could be promising avenues for further research.

6.2. Practical implications

As we have shown, TK has no direct effect on Use. TK in isolation may neither be sufficient to teach with technology nor about technology. Thus, in teacher education and training TPK and TPACK may be brought into focus. However, TK seems to be conducive to TPK, TPACK, and TCoK and, therefore, should not be neglected. Formative assessments could help to identify teachers with insufficient TK. Such teachers might receive offers for specific training. Overall, it could be advantageous to rely on an overarching framework for teacher and student TK that is accepted by the stakeholders, e.g., the DigComp framework. By means of this, teachers are trained in the same knowledge that they are also expected to foster among their students, e.g., efficient technology-supported collaboration, and complexity can be reduced. From the professional knowledge facets, only TPACK directly predicts the use of technology-related content. Hence, using technology as a content of instruction may require a specific kind of knowledge. Efforts towards TPACK development may build upon TK and TPK, i.e., TPACK is addressed after TPK ([Angeli & Valanides, 2009](#)).

As hypothesized, TCoK positively predicts TPK and TPACK. In a training setting teachers may be required to collaborate. This could be achieved by establishing online learning communities ([Zhang et al., 2019](#)). In this way, teachers could directly experience the advantages of collaboration for their professional development and form positive attitudes towards it. Since attitudes are important in predicting Use, they may be addressed in professional development programs as well. To this end, the usefulness and ease of use for the individual (prospective) teacher may be demonstrated ([Scherer et al., 2019](#)).

7. Outlook

[Scherer, Tondeur, Siddiq, and Baran \(2018\)](#) showed that positive attitudes towards technology are positively associated with TPACK. Hence, besides a direct influence on Use, positive attitudes may also have an indirect positive influence via TPACK, TPK, or TCoK. To consider such indirect paths could be an avenue for future research. Moreover, we investigated technology integration across subjects, which may be a reasonable starting point ([Sailer et al., 2021; this issue](#)). Qualitative research would be helpful to identify how technology integration manifests itself in various subjects. Based on this, specific questionnaires for specific subjects, e.g., business education or language learning, could be developed.

Due to the quantitative empirical character of our study, we addressed the current technological state as delineated by the DigComp 2.1 framework. However, the potential of artificial intelligence in education has not been fully exploited ([Luckin, Holmes, Griffiths, & Forcier, 2016](#)). An example for educational technology driven by artificial intelligence are chatbots ([Smutny & Schreiberova, 2020](#)) or social robots that assist teachers ([Papadopoulos et al., 2020; Guggemos, Seufert, & Sonderegger, 2020](#)). The fundamental difference of such smart machines (devices driven by artificial intelligence) from conventional technology may be that smart machines are no longer be regarded as a tool, but as a partner ([Daugherty & Wilson, 2018; Davenport & Kirby, 2016](#)). Currently, TK addresses how to use technology. However, for smart machines, collaboration could be a more appropriate conception. Just as

teachers need knowledge how to efficiently collaborate with human colleagues, they may need knowledge about collaborating with smart machines (concept of augmentation: Seufert, Guggemos, & Sailer, 2021). Daugherty and Wilson (2018) refer to such knowledge as *fusion skills*.

Assuming that fusion skills will become relevant in many areas and following our conceptual framework, teachers could be expected to foster those skills among their students, i.e., knowledge how to collaborate with smart machines. This may be well in line with initiatives in many countries to integrate computational thinking (Shute, Sun, & Asbell-Clarke, 2017; Wing, 2006) into curricula (Bocconi, Chiocciariello, Dettori, Ferrari, & Engelhardt, 2016). Among others, computational thinking aims at enabling students to take benefit from artificial intelligence (Gadanidis, 2017; Repenning, Webb, & Ioannidou, 2010).

Credit author statement

Josef Guggemos: Conceptualization, Methodology, Validation,

Appendix

S1

Items to capture the constructs.

Construct	No.	Item	λ	M	SD
Attitudes Technology	1	I like working with digital media in class	.92	5.37	1.34
	2	The use of digital media is very useful for me as a teacher	.83	5.55	1.37
Attitudes Content	3	I like to address basic knowledge about digitization in class ('computer science knowledge': principles of digitization, universal technologies)	.92	4.84	1.72
	4	I like to expand my professional knowledge in terms of digital transformation	.94	5.13	1.61
TCoK	5	As part of a department, I am able to create a common vision and strategy for the digital development of the school	.85	4.12	1.74
	6	I am able to create new digital modules, materials, or examinations in collaboration with other teachers	.89	4.57	1.73
	7	I can use databases to exchange knowledge (collection of good practices)	.79	4.09	1.76
	8	I can help to shape the organizational framework of the school (e.g., digital curriculum development in a team)	.75	3.62	1.89
TK	9	I can use advanced search strategies (e.g., search operators) to perform a search query on the Internet	.71	5.18	1.58
	10	I can create and edit digital content in different formats (e.g., PDF and PPTX)	.69	5.66	1.51
	11	I can use digital communication tools appropriately (e.g., online chat, instant messaging, blogs)	.73	4.20	1.81
	12	I know what to do if my computer is infected by malware	.59	5.01	1.75
	13	I have various strategies and ways to efficiently find a solution for technical problems with digital media	.72	5.01	1.64
TPK	14	I can validly assess the competence of my students with digital tools (competence diagnostics)	.80	3.89	1.53
	15	I can adapt my teaching with digital media depending on the students' learning progress (individualization according to learning progress)	.81	4.19	1.59
	16	I know how to avoid disruptions when teaching with digital media (classroom management)	.85	4.21	1.51
TPACK	17	I can use a wide range of different digital teaching and learning methods	.81	4.09	1.67
	18	I can select teaching-learning forms with digital media in order to effectively promote students' thinking and learning processes	.87	4.14	1.57
	19	I can use digital media in the classroom to promote the ability of students to find, understand, and evaluate online information	.79	4.68	1.35
	20	I can promote the use of digital media in the classroom to enable students to edit and create digital content	.88	4.27	1.52
	21	I can promote that students work together appropriately by adequate means in digital media lessons	.86	4.23	1.47
Use Technology	22	I can promote that students independently identify and solve problems using digital media	.80	4.03	1.56
	23	I can promote students' ability to use ICT applications (e.g., Microsoft Office ® package) in digital media lessons	.72	4.56	1.70
	24	Individualization of lessons according to learning progress using digital media	.83	2.23	1.27
Use Content	25	Blended learning scenarios (e.g., Flipped Classroom)	.57	1.75	0.98
	26	Digital teaching-learning forms in lessons	.85	2.94	1.32
	27	Topics of digitization in my teaching	.79	2.65	1.14
	28	Cross-disciplinary teaching on digitization topics	.74	1.83	0.93
	29	Promote interdisciplinary competencies of learners in dealing with digital media (e.g., dealing with online information)	.77	2.58	1.13

Note. Knowledge and attitudes related items (1–23) measured on seven-point scales of rating ranging from “does not apply at all” to “applies very strongly”. Use related items (24–29) measured with five-point scales of rating: never, infrequently (1–2 times per semester), occasionally (3–5 times per semester), frequently (every month), and very frequently (every week).

References

AERA, A. P. A., & NCME. (2014). *Standards for educational and psychological testing*. Washington D.C.: American Educational Research Association.
 Agyei, D. D., & Voogt, J. M. (2011). Exploring the potential of the will, skill, tool model in Ghana: Predicting prospective and practicing teachers' use of technology.

Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization, Project administration. Sabine Seufert: Conceptualization, Investigation, Writing - review & editing, Resources, Supervision, Funding acquisition

Acknowledgment

This work was supported by the State Secretariat for Education, Research and Innovation, Switzerland, (project DigiCompToTeach). Our thanks go to the nine schools that participated in this study. Moreover, we would like to thank the reviewers for the elaborate and thoughtful comments on previous versions of this paper. All statements expressed in this article are those of the authors and do not reflect the official opinions or policies of the authors' host affiliations or the supporting institution.

Computers & Education, 56(1), 91–100. <https://doi.org/10.1016/j.compedu.2010.08.017>
 Agyei, D. D., & Voogt, J. (2012). Developing technological pedagogical content knowledge in pre-service mathematics teachers through collaborative design. *Australasian Journal of Educational Technology*, 28(4). <https://doi.org/10.14742/ajet.827>

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- 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, 101300. <https://doi.org/10.1016/j.learninstruc.2019.101300>
- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182. <https://doi.org/10.1037/0022-3514.51.6.1173>
- Baumert, J., Kunter, M., Blum, W., Brunner, M., Voss, T., Jordan, A., ... Tsai, Y.-M. (2010). Teachers' mathematical knowledge, cognitive activation in the classroom, and student progress. *American Educational Research Journal*, 47(1), 133–180. <https://doi.org/10.3102/0002831209345157>
- Bell, A., Jones, K., & Fairbrother, M. (2018). Understanding and misunderstanding group mean centering: A commentary on Kelley et al.'s dangerous practice. *Quality and Quantity*, 52(5), 2031–2036. <https://doi.org/10.1007/s11135-017-0593-5>
- Bocconi, S., Chiocciariello, A., Dettori, G., Ferrari, A., & Engelhardt, K. (2016). *Developing computational thinking in compulsory education*. Luxembourg: Publications Office of the European Union. <https://doi.org/10.2791/792158>
- Borko, H. (2004). Professional development and teacher learning: Mapping the terrain. *Educational Researcher*, 33(8), 3–15. <https://doi.org/10.3102/0013189X033008003>
- Carretero, S., Vuorikari, R., & Punie, Y. (2017). *DigComp 2.1: The Digital Competence Framework for Citizens with eight proficiency levels and examples of use*. Luxembourg: European Union (EU). <https://doi.org/10.2760/38842>
- Christensen, R., & Knezek, G. (2008). Self-report measures and findings for information technology attitudes and competencies. In J. M. Voogt, & G. Knezek (Eds.), *International handbook of information technology in primary and secondary education* (pp. 349–365). Berlin: Springer.
- Claro, M., Salinas, A., Cabello-Hutt, T., San Martín, E., Preiss, D. D., Valenzuela, S., et al. (2018). Teaching in a Digital Environment (TIDE): Defining and measuring teachers' capacity to develop students' digital information and communication skills. *Computers & Education*, 121, 162–174. <https://doi.org/10.1016/j.compedu.2018.03.001>
- Conway, J. M., & Lance, C. E. (2010). What reviewers should expect from authors regarding common method bias in organizational research. *Journal of Business and Psychology*, 25(3), 325–334. <https://doi.org/10.1007/s10869-010-9181-6>
- Darling-Hammond, L., Newton, X., & Wei, R. C. (2010). Evaluating teacher education outcomes: A study of the stanford teacher education programme. *Journal of Education for Teaching*, 36(4), 369–388. <https://doi.org/10.1080/02607476.2010.513844>
- Daugherty, P. R., & Wilson, H. J. (2018). *Human + machine: Reimagining work in the age of AI*. La Vergne: Harvard Business Review Press.
- Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*. New York, NY: Harper Business.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319. <https://doi.org/10.2307/249008>
- Depaepe, F., & König, J. (2018). General pedagogical knowledge, self-efficacy and instructional practice: Disentangling their relationship in pre-service teacher education. *Teaching and Teacher Education*, 69, 177–190. <https://doi.org/10.1016/j.tate.2017.10.003>
- Dillenbourg, P. (2013). Design for classroom orchestration. *Computers & Education*, 69, 485–492. <https://doi.org/10.1016/j.compedu.2013.04.013>
- European Commission. (2019). *2nd survey of schools: ICT in education: Final report*. Luxembourg: Publications Office of the European Union. <https://doi.org/10.2759/23401>
- Farjon, D., Smits, A., & Voogt, J. M. (2019). Technology integration of pre-service teachers explained by attitudes and beliefs, competency, access, and experience. *Computers & Education*, 130, 81–93. <https://doi.org/10.1016/j.compedu.2018.11.010>
- Fraillon, J., Ainley, J., Schulz, W., Friedman, T., & Duckworth, D. (2019). *Preparing for life in a digital world: IEA international computer and information literacy study 2018 international report*. Amsterdam: International Association for the Evaluation of Educational Achievement (IEA). <https://www.iea.nl/publications/study-reports/preparing-life-digital-world>
- Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. *Internet Research*, 29(3), 430–447. <https://doi.org/10.1108/IntR-12-2017-0515>
- Gadanidis, G. (2017). Artificial intelligence, computational thinking, and mathematics education. *International Journal of Information and Learning Technology*, 34(2), 133–139. <https://doi.org/10.1108/IJILT-09-2016-0048>
- Gil-Flores, J., Rodríguez-Santero, J., & Torres-Gordillo, J.-J. (2017). Factors that explain the use of ICT in secondary-education classrooms: The role of teacher characteristics and school infrastructure. *Computers in Human Behavior*, 68, 441–449. <https://doi.org/10.1016/j.chb.2016.11.057>
- Graham, C. R. (2011). Theoretical considerations for understanding technological pedagogical content knowledge (TPACK). *Computers & Education*, 57(3), 1953–1960. <https://doi.org/10.1016/j.compedu.2011.04.010>
- Guggemos, J., Seufert, S., & Sonderegger, S. (2020). Humanoid robots in higher education: Evaluating the acceptance of Pepper in the context of an academic writing course using the UTAUT. *British Journal of Educational Technology*, 51(5), 1864–1883. <https://doi.org/10.1111/bjet.13006>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review*, 33(3), 405–431. <https://doi.org/10.1108/IMR-09-2014-0304>
- Hsu, L. (2016). Examining EFL teachers' technological pedagogical content knowledge and the adoption of mobile-assisted language learning: A partial least square approach. *Computer Assisted Language Learning*, 29(8), 1287–1297. <https://doi.org/10.1080/09588221.2016.1278024>
- Jia, F., & Wu, W. (2019). Evaluating methods for handling missing ordinal data in structural equation modeling. *Behavior Research Methods*, 51(5), 2337–2355. <https://doi.org/10.3758/s13428-018-1187-4>
- Kampylis, P., Punie, Y., & Devine, J. (2015). *Promoting effective digital-age learning: A European framework for digitally-competent educational organisations*. Luxembourg: European Union (EU). <https://doi.org/10.2791/54070>
- Kirschner, P. A. (2015). Do we need teachers as designers of technology enhanced learning? *Instructional Science*, 43(2), 309–322. <https://doi.org/10.1007/s11251-015-9346-9>
- Kirschner, P. A., & Bruyckere, P. de (2017). The myths of the digital native and the multitasker. *Teaching and Teacher Education*, 67, 135–142. <https://doi.org/10.1016/j.tate.2017.06.001>
- Knezek, G., & Christensen, R. (2016). Extending the will, skill, tool model of technology integration: Adding pedagogy as a new model construct. *Journal of Computing in Higher Education*, 28(3), 307–325. <https://doi.org/10.1007/s12528-016-9120-2>
- Koehler, M. J., & Mishra, P. (2009). What is technological pedagogical content knowledge? *Contemporary Issues in Technology and Teacher Education*, 9(1), 60–70.
- Koehler, M. J., Mishra, P., & Cain, W. (2013). What is technological pedagogical content knowledge (TPACK)? *Journal of Education*, 193(3), 13–19. <https://doi.org/10.1177/002205741319300303>
- Koh, J. H. L., Chai, C. S., & Tsai, C.-C. (2013). Examining practicing teachers' perceptions of technological pedagogical content knowledge (TPACK) pathways: A structural equation modeling approach. *Instructional Science*, 41(4), 793–809. <https://doi.org/10.1007/s11251-012-9249-y>
- Lawless, K. A., & Pellegrino, J. W. (2007). Professional development in integrating technology into teaching and learning: Knowns, unknowns, and ways to pursue better questions and answers. *Review of Educational Research*, 77(4), 575–614. <https://doi.org/10.3102/0034654307309921>
- Loncke, J., Eichelsheim, V. I., Branje, S. J. T., Buysse, A., Meeus, W. H. J., & Loeyts, T. (2018). Factor score regression with social relations model components: A case study exploring antecedents and consequences of perceived support in families. *Frontiers in Psychology*, 9, 1699. <https://doi.org/10.3389/fpsyg.2018.01699>
- Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. London: Pearson Education.
- Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, 108(6), 1017–1054.
- Nistor, N. (2014). When technology acceptance models won't work: Non-significant intention-behavior effects. *Computers in Human Behavior*, 34, 299–300. <https://doi.org/10.1016/j.chb.2014.02.052>
- Oberländer, M., Beinicke, A., & Bipp, T. (2020). Digital competencies: A review of the literature and applications in the workplace. *Computers & Education*, 146, 103752. <https://doi.org/10.1016/j.compedu.2019.103752>
- OECD. (2015). *Students, computers and learning*. Advance online publication. <https://doi.org/10.1787/9789264239555-en>
- Papadopoulos, L., Lazzarino, R., Miah, S., Weaver, T., Thomas, B., & Kouloughioti, C. (2020). A systematic review of socially assistive robots in pre-tertiary education. *Computers & Education*, 103924. <https://doi.org/10.1016/j.compedu.2020.103924>
- Pellegrino, J. W., DiBello, L. V., & Goldman, S. R. (2016). A Framework for conceptualizing and evaluating the validity of instructionally relevant assessments. *Educational Psychologist*, 51(1), 59–81. <https://doi.org/10.1080/00461520.2016.1145550>
- Petko, D. (2012). Teachers' pedagogical beliefs and their use of digital media in classrooms: Sharpening the focus of the 'will, skill, tool' model and integrating teachers' constructivist orientations. *Computers & Education*, 58(4), 1351–1359. <https://doi.org/10.1016/j.compedu.2011.12.013>
- Petko, D. (2020). Quo vadis TPACK? Scouting the road ahead. *EdMedia + Innovate Learning*, 23, 1277–1286.
- Praetorius, A.-K., Pauli, C., Reusser, K., Rakoczy, K., & Klieme, E. (2014). One lesson is all you need? Stability of instructional quality across lessons. *Learning and Instruction*, 31, 2–12. <https://doi.org/10.1016/j.learninstruc.2013.12.002>
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879–891. <https://doi.org/10.3758/brm.40.3.879>
- Prenger, R., Poortman, C. L., & Handelzalts, A. (2019). The effects of networked professional learning communities. *Journal of Teacher Education*, 70(5), 441–452. <https://doi.org/10.1177/0022487117753574>
- Redecker, C. (2017). *European framework for the digital competence of educators: DigCompEdu*. Luxembourg: Publications Office of the European Union. <https://doi.org/10.2760/159770>
- Repenning, A., Webb, D., & Ioannidou, A. (2010). Scalable game design and the development of a checklist for getting computational thinking into public schools. In G. Lewandowski, S. Wolfman, T. J. Cortina, & E. L. Walker (Eds.), *Proceedings of the 41st ACM technical symposium on computer science education - sigcse* (Vol. 10, p. 265). New York, New York, USA: ACM Press. <https://doi.org/10.1145/1734263.1734357>
- Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48(2), 1–36. <https://doi.org/10.18637/jss.v048.i02>

- Ryan, R. M., & Weinstein, N. (2009). A self-determination theory perspective on high-stakes testing. *Theory and Research in Education*, 7(2), 224–233. <https://doi.org/10.1177/1477878509104327>
- Saris, W. E., Satorra, A., & van der Veld, W. M. (2009). Testing structural equation models or detection of misspecifications? *Structural Equation Modeling: A Multidisciplinary Journal*, 16(4), 561–582. <https://doi.org/10.1080/10705510903203433>
- Sarstedt, M., Becker, J.-M., Ringle, C. M., & Schwaiger, M. (2011). Uncovering and treating unobserved heterogeneity with Fimix-PLS: Which model selection criterion provides an appropriate number of segments? *Schmalenbach Business Review*, 63, 34–62. <https://doi.org/10.1007/BF03396886>
- Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research*, 69(10), 3998–4010. <https://doi.org/10.1016/j.jbusres.2016.06.007>
- Satorra, A., & Bentler, P. M. (2010). Ensuring positiveness of the scaled difference chi-square test statistic. *Psychometrika*, 75(2), 243–248. <https://doi.org/10.1007/s11336-009-9135-y>
- Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (tam): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, 128, 13–35. <https://doi.org/10.1016/j.compedu.2018.09.009>
- Scherer, R., Siddiq, F., & Tondeur, J. (2020). All the same or different? Revisiting measures of teachers' technology acceptance. *Computers & Education*, 143, 103656. <https://doi.org/10.1016/j.compedu.2019.103656>
- Scherer, R., Tondeur, J., & Siddiq, F. (2017). On the quest for validity: Testing the factor structure and measurement invariance of the technology-dimensions in the Technological, Pedagogical, and Content Knowledge (TPACK) model. *Computers & Education*, 112, 1–17. <https://doi.org/10.1016/j.compedu.2017.04.012>
- Scherer, R., Tondeur, J., Siddiq, F., & Baran, E. (2018). The importance of attitudes toward technology for pre-service teachers' technological, pedagogical, and content knowledge: Comparing structural equation modeling approaches. *Computers in Human Behavior*, 80, 67–80. <https://doi.org/10.1016/j.chb.2017.11.003>
- Schmid, M., Brianza, E., & Petko, D. (2020). Developing a short assessment instrument for Technological Pedagogical Content Knowledge (TPACK.xs) and comparing the factor structure of an integrative and a transformative model. *Computers & Education*, 157, 103967. <https://doi.org/10.1016/j.compedu.2020.103967>
- Schmidt, D. A., Baran, E., Thompson, A. D., Mishra, P., Koehler, M. J., & Shin, T. S. (2009). Technological pedagogical content knowledge (TPACK). *Journal of Research on Technology in Education*, 42(2), 123–149. <https://doi.org/10.1080/15391523.2009.10782544>
- Seufert, S., Guggemos, J., & Sailer, M. (2021). Technology-related knowledge, skills, and attitudes of pre- and in-service teachers: The current situation and emerging trends. *Computers in Human Behavior*, 115. <https://doi.org/10.1016/j.chb.2020.106552>. In this issue.
- Seufert, S., Guggemos, J., Tarantini, E., & Schumann, S. (2019). Developing and validating a framework of digital competencies for teachers in the commercial domain. *Zeitschrift für Berufs- und Wirtschaftspädagogik*, 115(2), 312–339. <https://doi.org/10.25162/ZBW-2019-0013>
- Shulman, L. S. (1986). Those who understand: Knowledge growth in teaching. *Educational Researcher*, 15(2), 4–14. <https://doi.org/10.3102/0013189X015002004>
- Shulman, L. S. (1987). Knowledge and teaching: Foundations of the new reform. *Harvard Educational Review*, 57(1), 1–23. <https://doi.org/10.17763/haer.57.1.j463w79r56455411>
- Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review*, 22, 142–158. <https://doi.org/10.1016/j.edurev.2017.09.003>
- Siddiq, F., Scherer, R., & Tondeur, J. (2016). Teachers' emphasis on developing students' digital information and communication skills (TEDDICS): A new construct in 21st century education. *Computers & Education*, 92–93, 1–14. <https://doi.org/10.1016/j.compedu.2015.10.006>
- Smutny, P., & Schreiberova, P. (2020). Chatbots for learning: A review of educational chatbots for the facebook messenger. *Computers & Education*, 151, 103862. <https://doi.org/10.1016/j.compedu.2020.103862>
- Straub, E. T. (2009). Understanding technology adoption: Theory and future directions for informal learning. *Review of Educational Research*, 79(2), 625–649. <https://doi.org/10.3102/0034654308325896>
- Supovitz, J. A. (2002). Developing communities of instructional practice. *Teachers College Record*, 104(8), 1591–1626. <https://doi.org/10.1111/1467-9620.00214>
- Teo, T., & van Schaik, P. (2012). Understanding the intention to use technology by preservice teachers: An empirical test of competing theoretical models. *International Journal of Human-Computer Interaction*, 28(3), 178–188. <https://doi.org/10.1080/10447318.2011.581892>
- Tiede, J., Grafe, S., & Hobbs, R. (2015). Pedagogical media competencies of preservice teachers in Germany and the United States: A comparative analysis of theory and practice. *Peabody Journal of Education*, 90(4), 533–545. <https://doi.org/10.1080/0161956X.2015.1068083>
- Tondeur, J., van Braak, J., Siddiq, F., & Scherer, R. (2016). Time for a new approach to prepare future teachers for educational technology use: Its meaning and measurement. *Computers & Education*, 94, 134–150. <https://doi.org/10.1016/j.compedu.2015.11.009>
- Tseng, F.-C., & Kuo, F.-Y. (2014). A study of social participation and knowledge sharing in the teachers' online professional community of practice. *Computers & Education*, 72, 37–47. <https://doi.org/10.1016/j.compedu.2013.10.005>
- Valtonen, T., Sointu, E., Kukkonen, J., Kontkanen, S., Lambert, M. C., & Mäkitalo-Siegl, K. (2017). TPACK updated to measure pre-service teachers' twenty-first century skills. *Australasian Journal of Educational Technology*, 33(3). <https://doi.org/10.14742/ajet.3518>
- Van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & Haan, J. de (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*, 72, 577–588. <https://doi.org/10.1016/j.chb.2017.03.010>
- Vangrieken, K., Dochy, F., Raes, E., & Kynndt, E. (2015). Teacher collaboration: A systematic review. *Educational Research Review*, 15, 17–40. <https://doi.org/10.1016/j.edurev.2015.04.002>
- Vangrieken, K., Meredith, C., Packer, T., & Kynndt, E. (2017). Teacher communities as a context for professional development: A systematic review. *Teaching and Teacher Education*, 61, 47–59. <https://doi.org/10.1016/j.tate.2016.10.001>
- Van de Schoot, R., Lugtig, P., & Hox, J. (2012). A checklist for testing measurement invariance. *European Journal of Developmental Psychology*, 9(4), 486–492. <https://doi.org/10.1080/17405629.2012.686740>
- Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. <https://doi.org/10.2307/41410412>
- Voogt, J. M., Fisser, P., Pareja Roblin, N., 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>
- Voss, T., Kunter, M., & Baumert, J. (2011). Assessing teacher candidates' general pedagogical/psychological knowledge: Test construction and validation. *Journal of Educational Psychology*, 103(4), 952–969. <https://doi.org/10.1037/a0025125>
- Warwas, J., & Helm, C. (2018). Professional learning communities among vocational school teachers: Profiles and relations with instructional quality. *Teaching and Teacher Education*, 73, 43–55. <https://doi.org/10.1016/j.tate.2018.03.012>
- Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33–35. <https://doi.org/10.1145/1118178.1118215>
- Zhang, S., Liu, Q., & Cai, Z. (2019). Exploring primary school teachers' technological pedagogical content knowledge (TPACK) in online collaborative discourse: An epistemic network analysis. *British Journal of Educational Technology*, 50(6), 3437–3455. <https://doi.org/10.1111/bjet.12751>
- Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, 37(2), 197–206. <https://doi.org/10.1086/651257>