Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-025-05960-z OPEN

Relations between teachers' technology integration within ICAP modes with moderation effects: international perspective

Branko Anđić [1✉], Mirjana Maričić [2], Soeharto Soeharto[3], Filiz Mumcu [4], Robert Weinhandl[1], Zsolt Lavicza [1], Andreja Špernjak [5], Lukáš Rokos[6], Jan Vondruška[6] & Andrej Šorgo[7]

This international study used the Interactive-Constructive-Active-Passive (ICAP) framework to examine the relations between teachers' integration of technology (TI) within different forms of learning/engaging modes. This study also explores how teacher age, experience, gender, and social background relate to these ICAP modes. Data were collected from 2978 teachers from seven European countries and analysed through Covariance-Based Structural Equation (CBSEM) using MPLUS 8 software. The main findings of this study show strong relations among passive, active, constructive, and interactive learning/engaging modes. A notable finding is that teaching experience and socio-economic context significantly influence these TI patterns, which indicate a pronounced shift from passive to active mode among novice teachers and that teachers in lower-ICT contexts face additional barriers. These and other results are discussed in this paper.

[1] School of Education, Johannes Kepler University, Department of STEM Education, Altenberger Straße 69 4040 Linz. Standort. Science Park 5, Linz, Austria. [2] School of Education, University of Novi Sad, Department of Sciences and Management in Education Podgorička 4, Sombor, Republic of Serbia. [3] Research Center for Education, National Research and Innovation Agency (BRIN), Indonesia Gedung B.J. Habibie, Jl. M.H. Thamrin No. 8, Jakarta Pusat, Indonesia. [4] Faculty of Education, Manisa Celal Bayar University, Department of Computer Education and Instructional Technologies, Demirci, Türkiye. [5] Faculty of Natural Sciences and Mathematics, University of Maribor, Koroška cesta 160, Maribor, Slovenia. [6] Faculty of Education, Department of Biology, University of South Bohemia, Jeronýmova 10, České Budějovice, Czech Republic. [7] University of Maribor Slomškov trg 15, Maribor, Slovenia. ✉email: brankoan01@gmail.com

Introduction

The integration of digital technologies into education has significantly transformed educational practices, pedagogical skills, and learning dynamics, highlighting the significant impact of digital tools on education systems. However, the positive effects of any educational technology are not guaranteed, and there are many cases where the introduction of digital technologies in a classroom even has negative side effects (Zhao & Beghetto, 2024). Since teachers are the main actors in the introduction, adaptation, use, and rejection of digital technologies (Anđić et al. 2023; Anđić et al. 2024; Branko et al. 2023; Maričić et al. 2025; Maričić et al. 2023) within the classroom environment, their role as mediators between technology and learners should be carefully analysed. Therefore, it was the researchers' intention to address this research gap using the Interactive-Constructive-Active-Passive (ICAP) framework (Chi, 2009; Chi et al., 2018; Chi & Boucher, 2023) to investigate the relations between teachers' integration of technology (TI) within different forms of learning/engaging modes,

Hillmayr et al. (2020) indicate, based on a detailed review of 91 articles, that the use of digital technologies can have a medium positive impact on students' learning outcomes in mathematics and science. This meta-analysis confirms the positive contribution of digital technologies that previous meta-analyses (Ma et al. 2014; Cheung and Slavin 2011; Vogel et al. 2017) have pointed to, and also shows a slightly larger effect size compared to the previous ones. Hillmayr et al. (2020) suggest that one of the reasons for the larger effect size in their study could be the development of digital technologies, better user experience, and the development of digital skills of teachers and students. Recent meta-analysis (Ran et al. 2022) shows that the way the technology is used, the duration of its use, and the purpose it serves in the classroom significantly correlate extent of the impact of digital technologies on student learning outcomes.

Several literature reviews (Sung et al. 2016; Zheng et al. 2016; Gui et al. 2023) identify the importance of the approaches for employing digital technologies, and teaching-pedagogical techniques used by teachers in digital teaching is related to its contribution to learning outcomes. The way digital technologies are used should correspond deeply with cognition and its integration into teaching, which can improve student motivation, attitude, and achievement (Grimley et al. 2012; West 2012; Cussó-Calabuig et al. 2018). According to the latest meta-analysis findings (Wang et al. 2023) that encompassed 78 manuscripts shows the way digital technology is used, its contribution to teaching and students' learning outcomes may be moderated by the following factors: socioeconomic environment, teaching context, and type of pedagogy used. Based on a non-systematic literature review that included research on the contribution of technology to pre-university education, Timotheou et al. (2023) concluded that teachers' personal characteristics and professional development can shape the usability and effectiveness of digital technologies in the classroom. Those researchers also detected a lack of research that focuses on the relations between teachers' gender, experience, age, and socioeconomic background and the use of digital technologies in the classroom. Their findings also support an earlier systematic review (Cussó-Calabuig et al. 2018; Oliveira et al. 2019) that suggests that there is still a lack of high-quality evidence on the impact of teacher's personal characteristics, such as age and gender, on the use of digital technologies in teaching. Some of the recent research (Tolba & Youssef, 2022; Ayanwale et al., 2024) also suggests that gender is not the only factor that can predict teachers' use of technology, but teaching experience as well. Teachers with less experience are more likely to integrate technology into teaching than more experienced teachers.

Prior research suggests that the impact of digital technology on student learning outcomes varies depending on instructional modes and teacher characteristics such as age, gender, and experience. Younger and less experienced teachers tend to adopt more interactive and constructive approaches (Tolba & Youssef, 2022; Ayanwale et al., 2024), while more experienced teachers may rely more on passive methods (Antonietti et al., 2023). The ICAP framework (Chi, 2009; Chi et al., 2018) provides a theoretical basis for understanding these differences by categorizing learning activities into passive, active, constructive, and interactive modes (Kümmel et al., 2020; Buhari & Sari, 2022). Building on this, our study applies Covariance-Based Structural Equation Modelling (CBSEM) structural model analysis as presented in Fig. 1 to explore the relations between ICAP modes in technology-supported learning and examines how these relations are moderated by teachers' age, gender, experience, and social background. By addressing these factors, our study seeks to advance the understanding of how teachers' characteristics shape the interplay between ICAP modes in a technology-based learning environment. Despite the growing body of research on the integration of digital technologies in education, there is still limited large-scale, cross-national evidence on how teachers' individual characteristics (age, gender, experience, and socioeconomic background) shape the way they transition between different ICAP learning modes. Previous studies often focused either on students' outcomes (Hillmayr et al., 2020; Wang et al., 2023) or on isolated aspects of teacher characteristics (Antonietti et al., 2023; Timotheou et al., 2023), and were predominantly conducted within a single socioeconomic and cultural context, limiting their generalizability. This study addresses this gap by analysing data from 2,978 teachers across seven European countries, using Covariance-Based Structural Equation Modelling (CBSEM) to explore both the direct and moderated relationships among the ICAP modes.

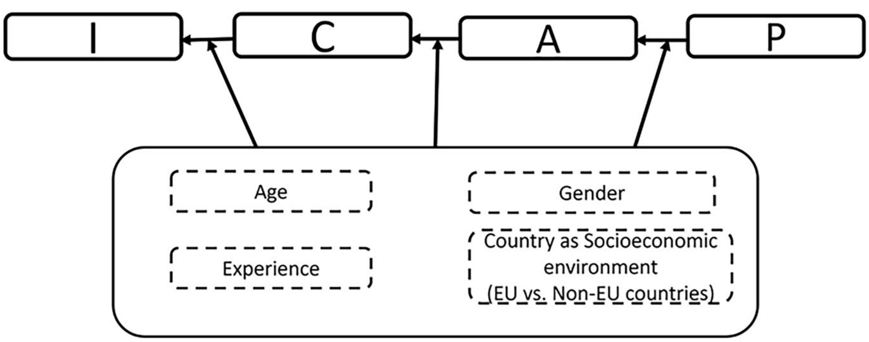

Fig. 1 Schematic representation of the research hypotheses (I-interactive, C-constructive, A-active, P-passive learning mode supported by educational technologies).

This study contributes to the literature in three important ways: (1) by providing one of the largest international datasets to date on teachers' technology integration practices, spanning both EU and non-EU contexts; (2) by examining, for the first time, how teacher characteristics such as experience, age, gender, and socioeconomic context moderate transitions between ICAP learning modes; and (3) by employing CBSEM to capture both direct and mediated pathways across ICAP dimensions. By clarifying these relationships, the study advances understanding of how contextual and personal factors shape teachers' adoption of more complex, cognitively demanding uses of educational technologies, informing both policy and professional development efforts. With this contribution to existing knowledge, this study not only expands the theoretical understanding of how teachers' characteristics interact with ICAP learning modes but also provides actionable insights for policymakers and professional development programmes. The findings can inform targeted training initiatives and resource allocation, especially in socioeconomically diverse contexts, to help teachers move beyond basic uses of technology and adopt more cognitively engaging practices.

Theoretical background

Understanding how teachers integrate digital technologies into their teaching is a key factor influencing educational outcomes. The ICAP framework has been widely adopted across various educational settings to classify learning activities and evaluate their effectiveness in technology-supported learning environments. This section of the manuscript provides an overview of the ICAP framework and ICAP Technology Scale (ICAP-TS), a tool developed in previous research to assess the use of digital technologies in the classroom.

The ICAP Framework

The ICAP framework provides a foundation for the exploration of students' cognitive engagement during active, passive, constructive, and interactive learning, with the aim of identifying concrete, explicit ways to encourage deeper cognitive processes (i.e., activation) (Chi 2009; Chi et al. 2018; Chi and Wylie 2014). It is generalisable across student age groups, content domains, and educational contexts. According to the ICAP framework, cognitive engagement is reflected in students' behaviour (i.e., interaction with learning material) based on specific cognitive processes, which range from passive to interactive and involved cognitive effort (Gobert et al. 2015). The ICAP framework has three key components: (1) the classification and description of the four modes of engagement, (2) the measurement of engagement levels based on cognitive behaviours associated with the modes, and (3) the generation of hypotheses predicting hierarchical levels of students' learning (Chi et al. 2018).

Within this framework, passive learning consists mainly of the receipt of information from teaching materials (e.g., by silent text reading, video viewing, and listening to online lectures), with students' behaviours reflecting their direction of attention to the materials and the acquisition of knowledge occurring only through information storage (Gobert et al. 2015). Active learning involves open actions or physical manipulation (e.g., gesturing while reading or undertaking tasks, pausing or rewinding videos, rotating objects, and underlining relevant text passages), and involves information storage, activation, and association (Chi et al. 2008; Yaron et al. 2010). Constructive (or generative) learning involves the generation of external ideas that include information beyond that provided in teaching materials, with students identifying similarities in and differences between presented concepts, engaging in self-explanation, communicating information in their own words, posing problems, and asking questions (Schauble et al. 2009; Schwartz et al. 2011). It involves all four basic cognitive processes: information storage, activation, association, and inference. Interactive learning involves communication between peers (or in small groups), with participants required to express constructive ideas (beyond the information provided), engage with their partners' contributions and co-generate contributions (i.e., collaborate) by building on, elaborating, and challenging each other's ideas (Antonietti et al. 2023). It involves all four basic cognitive processes, with inference extended to that gained from co-operation based on one's own and others' knowledge. It has the potential to create common understanding and creative solutions. The ICAP framework has been used to classify students' activities and interaction with digital technologies during learning in different contexts, with the ultimate goal of determining the quality of TI into teaching (Stegmann, 2020). This framework has served as the foundation for developing instruments to assess TI in teaching.

Assessing technology integration using ICAP technology scale

Wekerle et al. (2022) developed a 16-item scale based on the ICAP framework to assess students' perceptions of their engagement in technology-supported learning activities. Sailer et al. (2021) used an instrument based on scenarios collected from teachers to examine teachers' perspectives on new technology use (i.e., how often they would include technologies). This instrument has shown good reliability but has been argued to provide insufficient knowledge about TI according to the ICAP modes (Wekerle et al., 2022). Antonietti et al. (2023) recently developed the 12-item ICAP Technology Scale (ICAP-TS) for the assessment of teachers' TI according to the four dimensions of cognitive engagement (3 items each). TI is defined as technology use in an educational context to support academic goals and achieve learning outcomes, and related processes (Consoli et al. 2023). Its quality is reflected by users' ability to transform and redefine learning activities in processes that encourage cognitive activation or engagement (Fütterer et al. 2023). Cognitive activation is considered to be critical for successful learning and an essential element of teaching quality, with invisible aspects of teaching playing crucial roles in information processing and understanding (Fütterer et al. 2022). As part of the deep classroom structure, it is reflected in the ability of teachers' instructions (part of the visible surface structure) to encourage students' active cognitive engagement and higher-order thinking (Fütterer et al. 2023; Fütterer et al. 2022; Praetorius et al. 2018; Maričić et al. 2024).

Ninković et al. (2023) tested the ICAP-TS and investigated correlations among innovative school climates, principal support, and technology use for various ICAP activities. The teachers participating in the study often applied technology to students' passive learning, but not to the other three learning modes (Cai et al. 2017). In addition, the authors reported a strong positive correlation between constructive and interactive technology use in teaching, suggesting that these dimensions were not clearly distinguished and calling the discriminative validity of the scale into question (Ninković et al. 2023). This strong positive correlation suggests that teachers who frequently integrate technology for constructive learning (e.g., self-explanation, creating new knowledge) also tend to foster interactive learning (e.g., peer discussions, collaborative activities) (Ninković et al. 2023). Results of research done by Antonietti et al. (2023) indicated that gender and age of the respondents do not show significant differences in relation to the four dimensions of technological integration, nor in the overall score on the ICAP-TS scale. Nevertheless, the same study shows that teaching experience has a significant negative impact on the passive and interactive dimensions as well as on the overall score of the ICAP-TS assessment. The researchers emphasise the need for additional research that would investigate the relations of gender, age, and experience as moderating factors in the application of the ICAP-TS. The study (Ninković et al. 2023), however, does not present data on the influence of moderating factors such as gender, age, and experience, but the authors recommend including these aspects in future analyses. Meta-analyses (Ritter, 2017; Scherer & Teo, 2019) suggest that factors such as gender, age, and experience can significantly affect teachers' acceptance of technology and the quality of its implementation in the teaching process. These meta-analyses indicate that male teachers tend to report higher self-efficacy in using technology, while female teachers may adopt more pedagogically reflective approaches. Moreover, younger teachers are often more than their experienced colleagues open to experiment with digital technologies in teaching. These findings emphasize the importance of understanding how teachers' characteristics can correlate with the effectiveness of TI in the classroom. While several studies have examined the impact of digital technologies on student outcomes, to the best of our knowledge, there is a lack of large-scale international research specifically exploring how ICAP modes interact with one another and how this interaction is moderated by teacher characteristics such as age, experience, gender, and social background.

Research questions and hypotheses

This international study aims to investigate how the ICAP learning/engaging modes in technology-supported teaching are related and how the moderating effect influences the relations between ICAP dimensions, as depicted in Fig. 1. To address these research objectives, the following research questions and hypotheses have been formulated:

1. How do the relations between teachers TI into different ICAP mode dimensions vary based on direct and indirect effects within this international study context?
2. Do background variables, including age, gender, experience, and socioeconomic background (EU member states and non-EU countries), moderate the relations between different ICAP modes in technology-supported teaching?

The research model of our study is shown in Fig. 1. Antonietti et al. (2023) found that teaching experience has a significant negative impact on passive and interactive ICAP-TS assessments. Timotheou et al. (2023) and Wang et al. (2023) indicate that gender and age can also influence how teachers use technology in their teaching. Additionally, research by Wang et al. (2023), Perera and Aboal (2019), and Sung et al. (2016) suggests that the socioeconomic environment influences how teachers use digital technologies in teaching, which indicates there is a possible background variables interaction effect on ICAP modes.

Therefore, In accordance with the set research questions and a summary of the literature review on this topic, we propose the following hypotheses.

Direct effect hypotheses. H1: There is a significant relation between Passive and Active learning modes in the ICAP model.

H2: There is a significant relation between Active and Constructive learning modes in the ICAP model.

H3: There is a significant relation between Constructive and Interactive learning modes in the ICAP model.

Indirect (Mediated) effect. H4: Passive technology use influences Interactive learning mode through Active and Constructive learning modes as mediators.

H5: Active technology use influencesthe Interactive learning mode through the Constructive learning mode as a mediator.

Moderation effect. H6: Gender as a Moderator

H6a: Gender moderates the relation between Passive and Active learning modes in the ICAP model.

H6b: Gender moderates the relation between Active and Constructive learning mode in the ICAP model.

H6c: Gender moderates the relation between Constructive and Interactive learning mode in the ICAP model.

H7: Socioeconomic environment - Country as a Moderator

H7a: The effect of Passive learning mode on Active learning mode is moderated by socioeconomic environment;

H7b: The effect of Active learning mode on Constructive learning mode is moderated by socioeconomic environment.

H7c: The effect of the Constructive learning mode on the Interactive learning mode is moderated socioeconomic environment.

H9: Experience as a Moderator

H9a: Teaching experience moderates the relation between Passive and Active learning mode in the ICAP model.

H9b: Teaching experience moderates the relation between Active and Constructive learning modes in the ICAP model.

H9c: Teaching experience moderates the relations between Constructive and Interactive learning modes in the ICAP model.

H10: Age as a Moderator

H10a: Age moderates the relation between Passive and Active learning modes in the ICAP model.

H10b: Age moderates the relation between Active and Constructive learning mode in the ICAP model.

H10c: Age moderates the relation between Constructive and Interactive learning mode in the ICAP model.

Methodology

Data collecting procedure and sample characteristics. Teachers in seven European countries (Austria, the Czech Republic, Croatia, Montenegro, the Republic of Serbia, Slovenia, and Turkey) were invited to voluntarily participate in this study. When selecting the participating countries, in addition to existing research collaborations with scholars from these nations, consideration was given to including both EU member states and non-EU countries. Thus, in this study, Austria, the Czech Republic, Croatia, and Slovenia are members of the European Union, whereas Montenegro, the Republic of Serbia, and Turkey are not. The ICT Development Index (IDI) and the Digital Economy and Society Index (DESI), which assess a country's level of technological development (International Telecommunication Union, 2023), consider criteria such as connectivity, use of internet services, integration of digital technology, and digital public services. These factors influence the adoption of digital technologies in education and their implementation (Schmitz et al., 2023). According to the International Telecommunication Union (2024), Austria and Slovenia rank among the top performers in ICT development, while the Czech Republic and Croatia also demonstrate strong digital capabilities. However, Montenegro, the Republic of Serbia, and Turkey are ranked below 45th place, indicating the need for further improvements in the field of digitalization.

All participants in the study took part voluntarily. Anonymity and the protection of private data are guaranteed for all participants through anonymisation methods (PII data such as names, addresses, telephone numbers or similar are not collected from the participants). Using the snowball method (Cohen et al. 2002), data were collected over a 3-month period from primary-school (student age 6–10 years) and lower secondary school (student age 10–14.5 years) teachers in all countries. The email addresses of school principals in all countries were obtained from schools' official websites and ministries of education, and an email explaining the purpose of the study and including an online survey link was sent to the principals for forwarding to eligible teachers. A friendly reminder was sent to the same email addresses 3 weeks after the first email, and the survey was closed 3 weeks thereafter. The research involved teachers at different career stages through the phases of beginning teaching (0–5 years), developing pedagogical skills (5–10 years), gaining expertise (10–15 years) and mature career teachers (more than 20 years), which involves adaptation, experimentation, mentoring and continuous improvement over time. This classification of teachers into career groups was based on the recommendations of previous research by Coppe et al. (2024), Eros (2011), and Torenbeek and Peters (2017). Their findings suggest that teachers in the early stages of their careers, and next phases, develop pedagogical skills and gain expertise, and are more inclined to adopt innovative pedagogies and technologies. In contrast, those with 20 or more years of experience often have established didactic approaches that generally remain unchanged. These studies also highlight the importance of researching teachers' attitudes toward educational approaches and technologies during the early and middle stages of their careers. At these stages, teachers' opinions and attitudes are more adaptable and can be influenced more easily compared to those in later career stages.

Survey data were collected from 2978 teachers. After excluding incomplete surveys with more than 10% missing data, responses from 2277 teachers were included in the final analysis. Using the MPLUS 8 software, the Full Information Maximum Likelihood (FIML) estimation method was applied in the initial data analysis. Missing data were coded as (−999), and pattern analysis was conducted to examine potential missing data values in preparation for SEM analysis. The results confirmed that no data points had more than 10% missing data, meeting the threshold for conducting SEM analysis in this study. The comprehensive data analysis procedures employed in this study enhance the robustness of the findings. The sample size power was calculated using the Raosoft programme, applying key statistical parameters to ensure accuracy. The minimum required sample size was determined based on a 5% margin of error, a 99% confidence level, an assumed population of 20,000 teachers, and a 50% response distribution. The calculation resulted in a recommended minimum sample size of 377 participants. Given that the sample size used in this study exceeds this threshold, it can be concluded that the study has an adequate sample size to ensure representative and reliable findings.

Survey instrument. The survey includes an introduction and two main parts. The introduction informs respondents about the purpose of the research and the scope of information and communications technology in educational environments (including computers, projectors, laptops, tablets, smartphones, digital cameras, and relevant platforms and software). The first main part collects demographic data, such as gender, age, teaching experience, and socioeconomic background, from respondents. The second part is the 12-item ICAP-TS, which assesses the frequency of teachers' TI for activities in the four ICAP learning modes. Each learning mode is evaluated with three items. The items describe passive (i.e., showing and explaining instructional content with students in receptive mode), active (i.e., students applying prior knowledge and teachers' and students' active technology use), constructive (i.e., students using technology to acquire new knowledge), and interactive (i.e., students developing new knowledge through cooperation and collaboration) activities. For example, one item assessing active learning asks teachers to rate on a five-point scale how frequently (between 1—almost never to 5—almost every lesson) they engage students in activities. The reliability coefficients (Cronbach's alpha) for the ICAP-TS in the original study (Antonietti et al. 2023) across the subscales indicate good internal consistency, with values of 0.808 for the passive subscale, 0.867 for the active subscale, 0.893 for the constructive subscale, and 0.896 for the interactive subscale.

Permission was obtained from the scale's authors (Antonietti et al. 2023) to translate it into the native languages of the participating teachers. The translation was conducted by the researchers and verified by official translators (linguistic experts) in each country. An educational research expert in each country assessed the translated instrument's clarity, and improvements were made based on this feedback. Subsequently, 10 teachers in each country evaluated the scale's meaningfulness, relevance, and clarity, leading to the creation of the final versions based on their input. The feedback from the researchers and teachers was linguistic, grammatical, and syntactic, ensuring the instruments' clarity and consistency with the original (Antonietti et al. 2023).

Data analysis. The Covariance-Based Structural Equation (CBSEM) Modelling was used by utilizing MPLUS 8 software (Muthén & Muthén, 2018) to answer the research questions and investigate the hypotheses in this study. First, we specified the path model based on the ICAP theoretical framework and tested hypotheses H1–H10. The model included 12 items as observed variables measuring technology integration across different learning modes (passive, active, constructive, interactive). SEM modelling was employed to capture the underlying constructs of the ICAP learning modes. A SEM model is a set of constructs connected to a set of observed variables, also known as measurement or indicator variables (Hair et al. 2010). Given the non-normal distribution of variables, confirmed by the Kolmogorov–Smirnov and Shapiro–Wilk tests, we used the maximum likelihood (ML) estimation method to derive parameter estimates. The ML method is considered to be sufficiently robust to handle non-extreme deviations from normality, and it provides more informative results than the alternatives (Hair et al. 2010). ML parameter estimation was also considered appropriate because the model consists of only four indicators and 12 variables, and data were collected from a large group of participants.

We evaluated the fit of our model through several indices: $\chi 2$ = Chi-Square Test, AIC = Akaike Information Criteria, BIC = Bayesian Information Criteria, SRMR = Standardized Root Mean Square Residual, RMSEA = Root Mean Square Error of Approximation, CFI = Comparative Fit Index, TLI = Tucker–Lewis Index. Consequently, static fit indices were appropriate for evaluating the model fit in our dataset. Evaluation of model fit was used to assess one factor: Confirmatory Factor Analysis (CFA), Four Factor CFA, and the Structural model. The investigation of validity and reliability was evaluated based on factor loading values, Cronbach's Alpha (α), ω McDonald's omega (ω). The correlation between ICAP dimensions was also investigated using Pearson correlation. The strength and significance of direct and indirect paths between ICAP learning modes were calculated using a path coefficient standardized estimate (β). The moderation effects on the relationship between ICAP dimensions as latent factors were also investigated comprehensively.Fig. 2

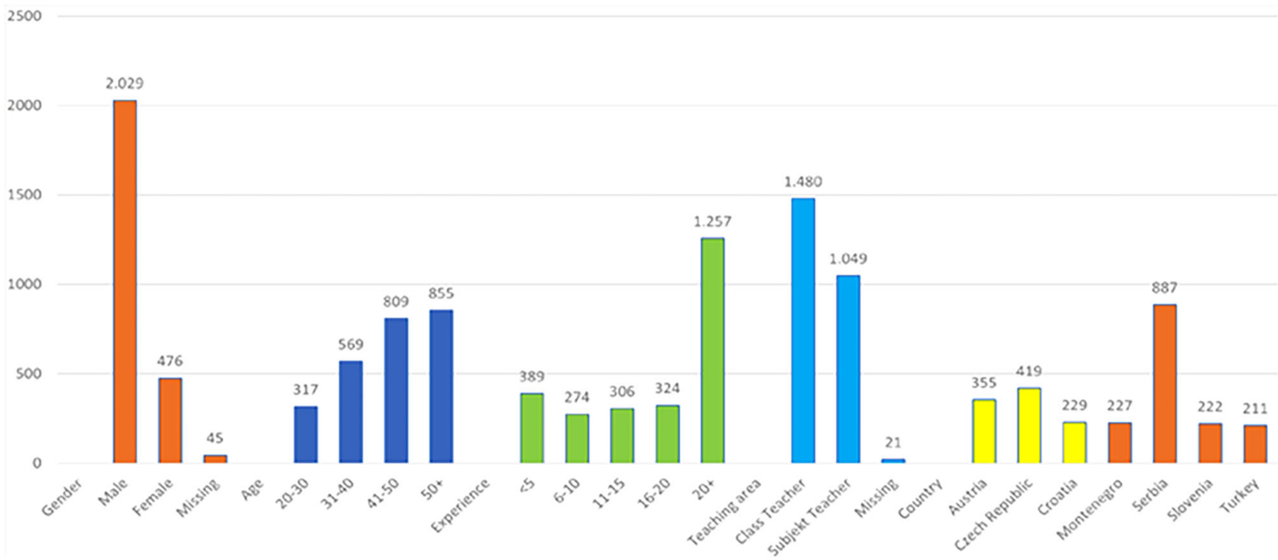

Fig. 2 Sample characteristics ($n = 2{,}277$).

Table 1 Model fit indices comparison in this study.

Model	χ2	df	χ2/df	AIC	BCI	SRMR	TLI	CFI	RMSEA (90%CI)
CFC						≤0.08	≥0.90	≥0.90	≤0.08
CFA one factor	4439.71***	54	82.22	74830.08	75036.38	0.087	0.707	0.760	0.18 (0.184 – 0.194)
CFA four factor	623.178***	48	12.98	71025.54	71266.23	0.039	0.967	0.969	0.07 (0.068 – 0.078)
Structural model	653.603***	51	12.82	71049.97	71273.46	0.043	0.967	0.967	0.07 (0.067 – 0.077)

*n = 2277. ***p 0.001. χ2 = Chi-Square Test, *df* Degrees of Freedom, *AIC* Akaike Information Criteria, *BIC* Bayesian Information Criteria, *SRMR* Standardized Root Mean Square Residual, *RMSEA* Root Mean Square Error Of Approximation, *CFI* Comparative Fit Index, *TLI* Tucker–Lewis Index, *CFC* Cut-off criteria (Byrne, 2016).

Results

The evaluation of model fit indices. This study employed a structural model to examine the relations among latent constructs, and its fit is evaluated in comparison to three alternative model fit indices: a one-factor confirmatory factor analysis (CFA) model, a four-factor CFA model, and a structural model. The assessment of model fit relies on widely accepted fit indices, including the Standardized Root Mean Square Residual (SRMR), Tucker–Lewis Index (TLI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA), based on the cut-off criteria proposed by Byrne (2016) as presented in Table 1. According to these criteria, a well-fitting model should exhibit an SRMR of ≤0.08, TLI and CFI values of ≥0.90, and an RMSEA of ≤ 0.08. The results indicate that the one-factor CFA model demonstrates poor fit, as evidenced by a high chi-square to degrees of freedom ratio (χ^2/df = 82.22), an SRMR value of 0.087 (exceeding the acceptable threshold), and low incremental fit indices (TLI = 0.707, CFI = 0.760). Additionally, the RMSEA value of 0.18 (90% CI: 0.184–0.194) is substantially higher than the recommended upper limit, suggesting that the model fails to adequately represent the data. These findings indicate that a single-factor structure is insufficient in capturing the underlying relationships among the constructs. Conversely, the four-factor CFA model exhibits a significantly improved fit, with a χ^2/df ratio of 12.98 and an SRMR of 0.039, which falls within the acceptable range. Furthermore, the TLI (0.967) and CFI (0.969) exceed the recommended threshold of 0.90, indicating strong incremental fit. The RMSEA value of 0.07 (90% CI: 0.068–0.078) further supports the adequacy of the model, confirming that a multidimensional structure better represents the data

The structural model as presented in Fig. 3, which serves as the primary analytical framework in this study, demonstrates a better fit than the four-factor CFA model. The χ^2/df ratio of 12.82 is closed to that of the four-factor model, while the SRMR value of 0.043 remains well within the acceptable range. The TLI and CFI values of 0.967 further indicate strong incremental fit, while the RMSEA value of 0.07 (90% CI: 0.067–0.077) aligns with recommended criteria by Byrne (2013, 2016). Given that the structural model integrates both direct, indirect, and moderation effects among latent constructs, these findings validate its suitability for hypothesis testing and theoretical examination.

Validity and reliability criteria. The validity and reliability of the ICAP dimensions in the structural model were assessed using standardized factor loadings (SFL) for validity and Cronbach's alpha (α) and McDonald's omega (ω) for reliability. Standardized factor loadings above 0.50 indicate strong construct validity as recommendation from Kock (2014). The Interactive construct showed strong loadings (0.823–0.847), confirming that its items effectively measure the construct. Similarly, the Constructive construct demonstrated high loadings (0.852–0.875). The Active construct exhibited moderate to strong factor loadings, with Active1 (0.578) being notably lower than Active2 and Active3. The Passive construct displayed acceptable loadings (0.652–0.884), with Passive1 (0.652) being the lowest but within an acceptable range. Reliability was evaluated using Cronbach's alpha (α) and McDonald's omega (ω), with values above 0.70 indicating good internal consistency (Dunn et al., 2014; Taber, 2018). The overall ICAP instrument demonstrated excellent reliability (α = 0.921, ω = 0.918). At the construct level, Interactive (α = 0.877, ω = 0.878) and Constructive (α = 0.897,

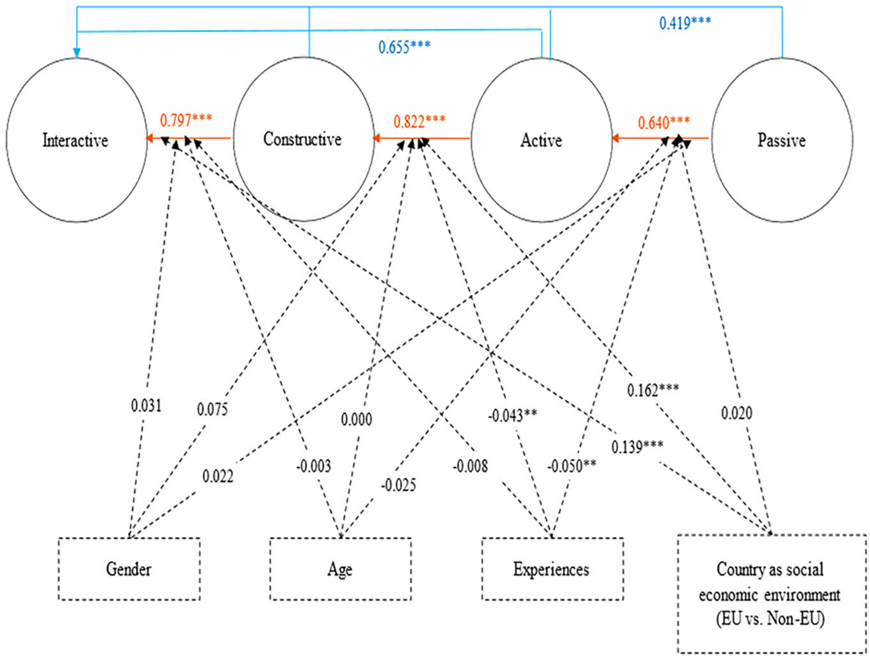

Fig. 3 The structural model result based on CBSEM analysis.

Table 2 Loading Factors, Reliability, Mean, SD values based on dimensions in structural model.

Construct	Item	SFL	Mean	SD	α	ω
ICAP (Instrument)			3.040	0.8972	0.921	0.918
Interactive			2.853	1.10323	0.877	0.878
	Interac1	0.823				
	Interac2	0.847				
	Interac3	0.847				
Constructive			2.9072	1.13219	0.897	0.898
	Const1	0.858				
	Const2	0.875				
	Const3	0.852				
Active			3.4873	1.04437	0.809	0.820
	Active1	0.578				
	Active2	0.854				
	Active3	0.884				
Passive			2.9183	1.04943	0.838	0.844
	Passive1	0.652				
	Passive2	0.877				
	Passive3	0.884				

*SFL Standardized Factor Loading, α Cronbach's Alpha, ω McDonald's omega, SD Standard deviation, Mean The average of observed items.

Table 3 Pearson correlation between dimensions of ICAP.

	1	2	3	4
1. Interactive				
2. Constructive	0.789***			
3. Active	0.687***	0.808***		
4. Passive	0.442***	0.560***	0.628***	

$n = 2277$. $^{***}p < 0.001$.

ω = 0.898) exhibited strong reliability. The Active construct (α = 0.809, ω = 0.820) had slightly lower but acceptable reliability, possibly influenced by the lower loading of Active1. The Passive construct (α = 0.838, ω = 0.844) also showed strong internal consistency. These results indicate that the ICAP model is well-supported, with strong construct validity and high internal consistency across all dimensions as presented in Table 2.

The relations among ICAP dimensions. To assess the relations among ICAP dimensions, the Pearson correlation analysis in Table 3 confirms the relationships between the four dimensions of the ICAP model: Interactive, Constructive, Active, and Passive.

The correlation coefficient is interpreted based on its strength as recommendation of Berman (2016) as follow: a coefficient of 0.8 or higher indicates a very high correlation, while values between 0.6 and 0.79 represent a moderate correlation. Correlations ranging from 0.3 to 0.59 are considered fair, whereas coefficients below 0.3 indicate a poor correlation. All correlation coefficients are statistically significant at $p < .001$, indicating strong relations among the constructs. The strongest correlation is observed between Constructive and Active dimensions ($r = 0.808$). The Interactive dimension also shows a high correlation with Constructive ($r = 0.789$) and a moderate correlation with Active ($r = 0.687$). The Passive dimension, as expected, has the weakest correlations with the other three dimensions. It is moderately correlated with Active ($r = 0.628$) and Constructive ($r = 0.560$), while its correlation with Interactive ($r = 0.442$) is the lowest among all relations. Overall, the correlation matrix supports the hierarchical nature of the ICAP model for the international study context.

The structural path analysis presented in Table 4 confirms significant direct effects among the ICAP technology model dimensions. The results indicate a strong and positive relation between Passive and Active technology use ($\beta = 0.640$, $p < 0.001$), Active and Constructive technology use ($\beta = 0.822$, $p < 0.001$), and Constructive and Interactive technology use ($\beta = 0.797$, $p < 0.001$). The significant direct effects suggest that teachers' integration of technology in passive learning can facilitate more active engagement, which in turn fosters constructive learning and eventually promotes interactive learning activities. The high

Table 4 Direct, indirect, and moderation effects.

H1-H65	Structural path	estimate(β)	S.E.	Est./S.E.	p value	Conclusion
Direct Effect						
H1	Passive → Active (+)	0.640	0.015	41.79	0.000***	Supported
H2	Active → Constructive (+)	0.822	0.010	84.413	0.000***	Supported
H3	Constructive → Interactive (+)	0.797	0.011	75.762	0.000***	Supported
Indirect effect (mediation)						
H4	Passive → Active → Constructive → Interactive (+)	0.419	0.014	30.197	0.000***	Supported
H5	Active → Constructive → Interactive (+)	0.655	0.013	51.974	0.000***	Supported
Moderation effect						
H6-Gender	Gender×Passive → Active	0.022	0.044	0.504	0.615	Not supported
	Gender×Active → Constructive	0.075	0.062	1.213	0.225	Not supported
	Gender×Constructive → Interactive	0.031	0.041	0.762	0.446	Not supported
H7-Countries	NonEU_EU×Passive → Active	0.020	0.018	1.160	0.246	Not supported
	NonEU_EU×Active → Constructive	0.162	0.024	2.577	0.010**	Supported
	NonEU_EU×Constructive → Interactive	0.139	0.017	8.385	0.011**	Supported
H9-Experience	Experience×Passive → Active	-0.050	0.020	-2.500	0.012**	Supported
	Experience×Active → Constructive	-0.043	0.016	-2.678	0.007**	Supported
	Experience×Constructive → Interactive	-0.008	0.017	0.123	0.614	Not supported
H10-Age	Age×Passive → Active	-0.025	0.018	-1.426	0.154	Not supported
	Age×Active → Constructive	0.000	0.016	0.014	0.989	Not supported
	Age×Constructive → Interactive	-0.003	0.016	-0.179	0.858	Not supported

$n = 2277$, ** $p < 0.05$, *** $p < 0.001$. estimate(β)= path coefficient, S:E standard error, p values Probability values.

path coefficients confirm the strength of these sequential relations, reinforcing the hierarchical structure of technology-supported learning under the ICAP framework. The indirect (mediated) effects further validate the cascading influence of technology use from Passive to Interactive learning mode. The mediation model confirms that the Passive learning mode use positively influences Interactive learning mode through the Active and Constructive learning mode as mediators ($\beta = 0.419$, $p < 0.001$). Similarly, Active learning mode significantly influences Interactive learning modes through the Constructive learning mode ($\beta = 0.655$, $p < 0.001$). These results indicate that while passive technology use alone may not directly enhance student interaction, it plays a foundational role in facilitating active and constructive technology integration, which ultimately leads to meaningful interactive engagement. The strong mediation effects highlight the necessity of a progressive, scaffolded approach to technology use in teaching, where higher-order cognitive engagement is achieved through well-structured active and constructive learning experiences.

The moderation effects reveal that only country and teaching experience significantly influence the structural relations, while gender and age do not exhibit any moderating influence. The results show that the relation between Active and Constructive is significantly moderated by country ($\beta = 0.062$, $p = 0.010$), as well as Constructive and Interactive learning mode ($\beta = 0.139$, $p < 0.001$). This suggests that teachers in different educational and technological contexts (EU vs. Non-EU) may integrate technology differently across ICAP modes. Additionally, teaching experience negatively moderates the relations between Passive and Active ($\beta = -0.050$, $p = 0.012$) and Active and Constructive technology use ($\beta = -0.043$, $p = 0.007$), indicating that more experienced teachers may be less inclined to transition between these ICAP learning modes. However, the Constructive to Interactive relation is not significantly affected by experience, suggesting that experienced teachers, once engaged in constructive learning, do not differ significantly from less experienced teachers in fostering the Interactive learning mode. These findings underscore the importance of considering contextual and experiential factors when designing professional development programmes for technology-enhanced teaching.

Discussion

The results of this international study, which was conducted on a sample of teachers from seven European countries, shed light on how technology is integrated into teaching according to different ICAP modes (Chi, 2009; Chi et al., 2018; Chi & Boucher 2023). How the dimensions of ICAP are hierarchically related and how certain characteristics of teachers (gender, age, experience, socioeconomic background) may moderate these relations were also investigated. These findings help bridge a notable gap in prior research, where most studies either concentrated on student outcomes or explored teacher characteristics in isolation, without considering how these factors jointly shape teachers' progression across ICAP learning modes in diverse socioeconomic contexts. By capturing these dynamics across seven countries, our study provides a more comprehensive understanding of how technology integration develops in practice and identifies where targeted interventions could support teachers in advancing toward more cognitively engaging uses of digital tools.

In our study, the structural model showed a strong and statistically significant direct effect between each neighbouring dimension, passive to active, from active to constructive, and from constructive to interactive, of the ICAP framework. At the same time, a significant indirect effect was observed: Passive use of technology "leads" to interactive use via active and constructive use, while active use also indirectly influences interactive use via constructive use. These results support previous research indicating that the use of technology in the classroom can be viewed as a process in which teachers and students first use basic-lower, less demanding digital activities and only then, under certain conditions, move on to more complex activities (Stegmann 2020; Ninković et al. 2023). The results of our study provide a more detailed picture of the factors that may moderate these relations. In line with previous findings (Wang et al. 2023; Timotheou et al. 2023), external factors, such as whether the teacher is from an EU member state or a non-EU country, were shown to have a significant moderating role on the relations between active and constructive and between constructive and interactive modes. In other words, depending on whether teachers are working-teaching in countries with different socio-economic indicators and different degrees of digital transformation, it is possible that the transition from active to constructive, i.e., from constructive to interactive work using technology does not occur with the same intensity. These findings complement the findings of Wang et al. (2023), Perera and Aboal (2019), and Sung et al. (2016), which suggest that the social and economic context, including the digital maturity level of the education system, may play an important role in teachers' adoption and use of digital tools. It is possible that in countries with a better socio-economic environment and a higher ICT development index, teachers can more easily switch from a passive to a constructive and interactive mode of technology use. This assumption is based on the results of our study as well as the findings of Teng et al. (2022) and Adebayo et al. (2020), which indicate that teachers in more developed countries have more resources that enable them to use digital technologies more effectively in the classroom than their colleagues from less developed socio-economic environment. Future research should investigate our hypothesis.

Regarding the relations between ICAP modes themselves, the obtained findings complement the broad base of literature on cognitive engagement (Kümmel et al. 2020; Giacomo et al. 2017; Yang et al. 2021). Namely, the assumption that teachers first use a passive mode of technology in teaching directing students to watch a video lesson or listen to a lecture with material projection, then an active one (e.g., pausing the recording, underlining key parts of the text, rewriting what they have learned). In order to reach interactive activities (e.g., cooperation, discussion and co-creation with the support of technology) through constructive approaches (e.g., creating new materials, asking questions that go beyond the assigned content), is thoroughly supports by this research. In accordance with the literature (Chi et al. 2018; Chi and Wylie 2014; Antonietti et al. 2023), we can conclude that the application of one ICAP mode can support the next. This, however, should not be interpreted as a strictly causal process, but as a model that describes the probability and frequency of transitions between different levels of cognitive engagement.

One particularly noteworthy finding concerns the moderating effect of experience. The results show that more year of teaching experience (more than 20 years) negatively moderates the relation between passive and active, as well as active and constructive mode, but not the relation between constructive and interactive teaching mode. Based on these results, it can be said that less experienced teachers are, on average, more inclined to "switch" from passive to active, and then from active to constructive mode. Similar tendencies were observed in some earlier studies (Tolba and Youssef 2022; Ayanwale et al. 2024), which also showed that younger or less experienced teachers more often report a willingness or habit to experiment with digital tools in order to more actively involve students. On the other hand, some authors, such as Antonietti et al. (2023), did not find a significant difference when it comes to age and gender, but did detect the effect of experience on certain dimensions of the ICAP, especially on passive and interactive mode. One possible explanation for the discrepancy between our results and those of Antonietti et al. (2023) is that we conducted our research in an international setting, whereas Antonietti et al. (2023) conducted theirs in Switzerland, a country characterized by a high level of digital and socioeconomic development. Future research should further investigate how age and work experience influence the ways in which teachers apply digital technologies in the classroom.

In our study, gender and age did not have a significant moderating role in the transition from passive to active, active to constructive or constructive to interactive mode. This is somewhat contrary to some previous works that emphasized that there are gender differences in the use of technology (Bosch and Laubscher 2019; Ayanwale et al. 2024), or that younger teachers are more inclined to integrate digital tools (Sung et al. 2016; Scherer et al. 2019). However, similar situations appear in earlier research, where the effect of gender or age was shown to be inconsistent (Antonietti et al. 2023). One possible explanation why these effects did not appear in our sample could be the diversity of the participating countries and their educational systems, different forms of initial education and professional work contexts. Also, in some environments, there may be an active digital infrastructure that benefits both older and younger teachers, that is, both women and men. However, it is important to emphasize that our results do not exclude the possibility that in some other contexts (e.g., other countries, with different technology) gender or age play a more significant role.

A very important implication of this study is the finding that the socioeconomic environment (membership in the EU versus countries outside the EU) moderates the transition from the active to the constructive and from the constructive to the interactive mode moderately but statistically significantly. Our results support the findings of Wang et al. (2023) as well as the findings of Chien et al. (2016) Perera and Aboal (2019) on the influence of the socioeconomic environment on the adoption of digital practices in the classroom. Furthermore, Timotheou et al. (2023) point out that even if the level of digital literacy improves in a country, cultural or structural elements (e.g., curriculum and syllabi, assessment policies, availability of technology) remain that can change the way and extent to which digital tools are used. In our sample, teachers from EU countries with better indicators of ICT development (e.g., Austria, Slovenia, Czech Republic, Croatia) were on average more willing to "upgrade" their methods from active to constructive learning using digital tools and then to an interactive approach. Nevertheless, teachers from non-EU countries with a lower ICT index (e.g., Turkey, the Republic of Serbia, Montenegro) also report positive relations between the ICAP dimensions mentioned, only that this is somewhat weaker. This result is in line with meta-analyses that indicate that the level of digital literacy and infrastructure varies, which directly affects how technology is integrated into the teaching process (Zheng et al. 2016; Gui et al. 2023). These findings add to the existing literature (Tolba and Youssef 2022; Ayanwale et al. 2024; Bosch and Laubscher 2019; Scherer et al. 2019), which suggests that socioeconomic environment is relevant factor in how much and how teachers switch between different cognitive modes when using technology in the classroom. These findings may be of importance to policymakers in developing countries as they suggest that teachers in these countries may need additional support as they move to more complex levels of digital technology use. By situating our findings within a large, cross-national dataset, this study helps address a key gap in the literature, where most prior research has either focused on a single socioeconomic context. Our results demonstrate not only the sequential progression teachers follow across ICAP modes, but also the critical role of experience and socioeconomic environment in shaping these transitions. These insights extend the current understanding of technology integration by clarifying which factors most influence teachers' ability to adopt more cognitively demanding practices, offering valuable guidance for future professional development initiatives and comparative research.

Conclusion and limitations

The results of this study show a clear and statistically significant progression from the passive to the active and constructive to the interactive mode in the ICAP model. This indicates when teachers start using technology in less demanding, passive mode, they can move relatively easily to active mode and then to deeper and more cognitively demanding dimensions - constructive and interactive. This confirms that the use of digital tools is a multilayered process that in practice often starts with basic, simpler activities and then, with some support and motivation, develops into increasingly complex approaches. In addition, the study shows that characteristics such as years of experience and socioeconomic context (EU countries vs. non-EU countries) can play an important role in the strength of these transitions. Differences in whether teachers work in countries with a higher or lower ICT index are also reflected in the nuances of the use of active, constructive, and interactive work. Teachers at the beginning of their career observed to move from passive to active and from active to constructive types of technology use to a greater extent, while experience played no role in the transition from constructive to interactive. However, the age and gender of the teacher in our sample showed no statistically significant moderation, suggesting that the possible effects of these factors may manifest selectively depending on the specific circumstances and characteristics of the educational system.

These findings hold important implications for teacher professional development and educational policy. Understanding how experience and socioeconomical context influence teachers' progression across ICAP modes can inform tailored training initiatives that help educators adopt more advanced, student-centred uses of technology. For policymakers, the results underscore the importance of addressing infrastructural and institutional barriers, particularly in lower-ICT environments, to support teachers in moving toward constructive and interactive practices.

This study also has several limitations. As a correlational study relying on teacher self-assessments, causal relationships cannot be inferred, and some discrepancies may exist between reported and actual classroom practices. Additionally, while the sample is large, it is unevenly distributed across countries, and certain contextual variables (such as internet availability, school-level technological support, and funding for equipment) were not included in the model. Future research should incorporate classroom observations, richer contextual measures, and longitudinal designs to provide a more comprehensive understanding of how ICAP modes develop and how they influence student outcomes.

Data availability

All data and materials, as well as software applications or custom code support published claims and comply with field standards. The data generated during and/or analysed during the current study are available from the corresponding author on request.

Received: 23 August 2024; Accepted: 8 September 2025;
Published online: 10 November 2025

References

Adebayo KA, Ntokozo N, Grace NZ (2020) Availability of educational resources and student academic performances in South Africa. Univers J Educ Res 8(8):3768–3781

Anđić B, Maričić M, Weinhandl R, Mumcu F, Schmidthaler E, Lavicza Z (2024) Metaphorical evolution: A longitudinal study of secondary school teachers' concepts of 3D modelling and printing in education. Educ Inf Technol 29(11):14091–14126. https://doi.org/10.1007/s10956-022-10005-0

Anđić B, Ulbrich E, Dana-Picard T, Cvjetićanin S, Petrović F, Lavicza Z, Maričić M (2023) A phenomenography study of STEM teachers' conceptions of using three-dimensional modeling and printing (3DMP) in teaching. J Sci Educ Technol 32(1):45–60

Antonietti C, Schmitz ML, Consoli T, Cattaneo A, Gonon P, Petko D (2023) Development and validation of the ICAP Technology Scale to measure how teachers integrate technology into learning activities. Comput Educ 192:104648

Ayanwale MA, Adelana OP, Odufuwa TT (2024) Exploring STEAM teachers' trust in AI-based educational technologies: A structural equation modelling approach. Discov Educ 3:1–22

Berman JJ (2016) Data simplification. Elsevier. https://doi.org/10.1016/C2015-0-00783-3

Bosch C, Laubscher DJ (2019) Cooperative learning as a strategy for self-directed learning in blended-distance learning environments: A systematic literature review. Student support toward self-directed learning in open and distributed environments 1–25

Branko A, Šorgo A, Helm C, Weinhandl R, Lang V (2023) Exploring factors affecting elementary school teachers' adoption of 3D printers in teaching. TechTrends 67(6):990–1006. https://doi.org/10.1007/s11528-023-00909-y

Buhari B, Sari RM (2022) Development of laboratory skills application based on android as a media of flipped learning model for nursing student. Malays J Nurs 14:30–35

Byrne BM (2013) Structural equation modeling with Mplus: Basic concepts, applications, and programming (1st ed.). Routledge. https://doi.org/10.4324/9780203807644

Byrne BM (2016) Structural equation modeling with AMOS. Routledge. https://doi.org/10.4324/9781315757421

Cai Z, Fan X, Du J (2017) Gender and attitudes toward technology use: A meta-analysis. Comput Educ 105:1–13

Cheung AC, Slavin RE (2011) The effectiveness of education technology for enhancing reading achievement: a meta-analysis. Center for Research and Reform in Education

Chi MT (2009) Active-constructive-interactive: a conceptual framework for differentiating learning activities. Top Cogn Sci 1:73–105

Chi MT, Boucher NS (2023) Applying the ICAP framework to improve classroom learning. In: In their own words: What scholars want you to know about why and how to apply the science of learning in your academic setting. American Psychological Association, pp 94–110

Chi MT, Adams J, Bogusch EB, Bruchok C, Kang S, Lancaster M, Yaghmourian DL (2018) Translating the ICAP theory of cognitive engagement into practice. Cogn Sci 42:1777–1832

Chi MT, Wylie R (2014) The ICAP framework: linking cognitive engagement to active learning outcomes. Educ Psychol 49:219–243

Chi MTH, Roy M, Hausmann RGM (2008) Observing tutoring collaboratively: Insights about tutoring effectiveness from vicarious learning. Cogn Sci 32:301–341

Chien YT, Chang YH, Chang CY (2016) Do we click in the right way? A meta-analytic review of clicker-integrated instruction. Educ Res Rev 17:1–18

Cohen L, Manion L, Morrison K (2002) Research methods in education. Routledge

Consoli T, Désiron J, Cattaneo A (2023) What is "technology integration" and how is it measured in K-12 education? A systematic review of survey instruments from 2010 to 2021. Comput Educ 10:42–47

Coppe T, Parmentier M, Kelchtermans G, Raemdonck I, März V, Colognesi S (2024) Beyond traditional narratives about teacher professional development: A critical perspective on teachers' working life. Teach Teach Educ 139:104436

Cussó-Calabuig R, Farran XC, Bosch-Capblanch X (2018) Effects of intensive use of computers in secondary school on gender differences in attitudes towards ICT: A systematic review. Educ Inf Technol 23:2111–2139

Dunn TJ, Baguley T, Brunsden V (2014) From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. Br J Psychol 105:399–412. https://doi.org/10.1111/bjop.12046

Eros J (2011) The career cycle and the second stage of teaching: Implications for policy and professional development. Arts Educ Policy Rev 112:65–70

Fütterer T, Hoch E, Lachner A, Scheiter K, Stürmer K (2023) High-quality digital distance teaching during COVID-19 school closures: Does familiarity with technology matter? Comput Educ 199:47–68

Fütterer T, Scheiter K, Cheng X, Stürmer K (2022) Quality beats frequency? Investigating students' effort in learning when introducing technology in classrooms. Contemp Educ Psychol 69:102042

Giacomo DD, Ranieri J, Lacasa P (2017) Digital learning as enhanced learning processing? Cognitive evidence for new insight of smart learning. Front Psychol 8:13–29

Gobert JD, Baker RS, Wixon MB (2015) Operationalizing and detecting disengagement within online science microworlds. Educ Psychol 50:43–57

Grimley M (2012) Digital leisure-time activities, cognition, learning behaviour and information literacy: what are our children learning? E-Learn Digit Media 9:13–28

Gui Y, Cai Z, Yang Y, Kong L, Fan X, Tai RH (2023) Effectiveness of digital educational game and game design in STEM learning: A meta-analytic review. Int J STEM Educ 10:1

Hair JF, Black WC, Babin BJ, Anderson RE (2010) Multivariate data analysis: A global perspective. 7th edn. Upper Saddle River, NJ: Prentice Hall

Hillmayr D, Ziernwald L, Reinhold F, Hofer SI, Reiss KM (2020) The potential of digital tools to enhance mathematics and science learning in secondary schools: A context-specific meta-analysis. Comput Educ 153:103897

International Telecommunication Union (2023) Measuring digital development: Facts and figures 2023. https://www.itu.int/itu-d/reports/statistics/facts-figures-2023/

International Telecommunication Union (2024) Measuring digital development: Facts and figures 2024. https://www.itu.int/en/ITU-D/Statistics/pages/facts/default.aspxKezar A (2006) The impact of institutional size on student engagement. NASPA J 43:87–114

Kock N (2014) Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM. Int J E-Collab 10:1–13

Kümmel E et al. (2020) Digital learning environments in higher education: a literature review of the role of individual vs. social settings for measuring learning outcomes. Educ Sci 10:78

Ma W, Adesope OO, Nesbit JC, Liu Q (2014) Intelligent tutoring systems and learning outcomes: a meta-analysis. J Educ Psychol 106:901–901

Maričić, M., Anđić, B., Mumcu, F., Rokos, L., Vondruška, J., Weinhandl, R., … & Špernjak, A. (2024) Evaluating the quality of technology integration across seven European countries with the ICAP Technology Scale. Journal of Computers in Education, 1-38. https://doi.org/10.1007/s40692-024-00341-y

Maričić M, Anđić B, Soeharto S, Mumcu F, Cvjetićanin S, Lavicza Z (2025) The exploration of continuous teaching intention in emerging-technology environments through perceived cognitive load, usability, and teacher's attitudes. Educ Inf Technol 30(7):9341–9370. https://doi.org/10.1007/s10639-024-13141-9

Maričić M, Cvjetićanin S, Anđić B, Marić M, Petojević A (2023) Using instructive simulations to teach young students simple science concepts: Evidence from electricity content. J Res Technol Educ 56(6):691–710. https://doi.org/10.1080/15391523.2023.2196460

Muthén B, Muthén L (2018) Mplus user's guide and diagrammer documentation. The Comprehensive Modelling Program for Applied Researchers: User's Guide, 5

Ninković S, Florić OK, Momčilović M (2023) Multilevel analysis of the effects of principal support and innovative school climate on the integration of technology in learning activities. Comput Educ 202:104833

Oliveira A, Feyzi Behnagh R, Ni L, Mohsinah AA, Burgess KJ, Guo L (2019) Emerging technologies as pedagogical tools for teaching and learning science: a literature review. Hum Behav Emerg Technol 1:149–16

Praetorius AK, Klieme E, Herbert B, Pinger P (2018) Generic dimensions of teaching quality: The German framework of three basic dimensions. ZDM Math Educ 50:407–426

Perera M, Aboal D (2019) The impact of a mathematics computer-assisted learning platform on students' mathematics test scores. Maastricht Economic and Social Research Institute on Innovation and Technology (UNU-MERIT). https://www.merit.unu.edu/publications/wppdf/2019/wp2019-007.pdf

Ran H, Kim NJ, Secada WG (2022) A meta-analysis on the effects of technology's functions and roles on students' mathematics achievement in K-12 classrooms. J Comput Assist Learn 38:258–284

Ritter LN (2017) Technology acceptance model of online learning management systems in higher education: a meta-analytic structural equation mode. l Int J Learn Manag Syst 5:1–16

Sailer M, Stadler M, Schultz-Pernice F, Franke U, Schöffmann C, Paniotova V, Fischer F (2021) Technology-related teaching skills and attitudes: validation of a scenario-based self-assessment instrument for teachers. Comput Hum Behav 115:106635

Schauble L, Glaser R, Duschl RA, Schulze S, John J (2009) Students' understanding of the objectives and procedures of experimentation in the science classroom. J Learn Sci 4:131–166

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. Comput Educ 128:13–35

Scherer R, Teo T (2019) Unpacking teachers' intentions to integrate technology: a meta-analysis. Educ Res Rev 27:90–109

Schmitz ML, Antonietti C, Consoli T, Cattaneo A, Gonon P, Petko D (2023) Transformational leadership for technology integration in schools: Empowering teachers to use technology in a more demanding way. Comput Educ 204:1–15. https://doi.org/10.1016/j.compedu.2023.104880

Schwartz DL, Chase CC, Oppezzo MA, Chin DB (2011) Practicing versus inventing with contrasting cases: the effects of telling first on learning and transfer. J Educ Psychol 103:759–775

Stegmann K (2020) Effekte digitalen Lernens auf den Wissens- und Kompetenzenerwerb in der Schule: eine Integration metaanalytischer Befunde [Effects of digital learning for knowledge acquisition and competence development in school: an integration of meta-analytic evidence]. Z Padagogik 66:174–190

Sung YT, Chang KE, Liu TC (2016) The effects of integrating mobile devices with teaching and learning on students' learning performance: a meta-analysis and research synthesis. Comput Educ 94:252–275

Taber KS (2018) The use of Cronbach's alpha when developing and reporting research instruments in science education. Res Sci Educ 48:1273–1296. https://doi.org/10.1007/s11165-016-9602-2

Teng Z, Cai Y, Gao Y, Zhang X, Li X (2022) Factors affecting learners' adoption of an educational metaverse platform: An empirical study based on an extended UTAUT model. Mob Inf Syst 2022(1):5479215

Torenbeek M, Peters V (2017) Explaining attrition and decreased effectiveness of experienced teachers: A research synthesis. Work 57:397–407. https://doi.org/10.3233/wor-172575

Timotheou S, Miliou O, Dimitriadis Y, Sobrino SV, Giannoutsou N, Cachia R, Ioannou A (2023) Impacts of digital technologies on education and factors influencing schools' digital capacity and transformation: a literature review. Educ Inf Technol 28:6695–6726

Tolba EG, Youssef NH (2022) High school science teachers' acceptance of using distance education in the light of UTAUT. Eurasia J Math Sci Technol Educ 18

Vogel F, Wecker C, Kollar I, Fischer F (2017) Socio-cognitive scaffolding with computer-supported collaboration scripts: a meta-analysis. Educ Psychol Rev 29:477–511

Wang J, Tigelaar DE, Zhou T, Admiraal W (2023) The effects of mobile technology usage on cognitive, affective, and behavioural learning outcomes in primary and secondary education: a systematic review with meta-analysis. J Comput Assist Learn 39:301–328

Wekerle C, Daumiller M, Kollar I (2022) Using digital technology to promote higher education learning: the importance of different learning activities and their relations to learning outcomes. J Res Technol Educ 54:1–17

West DM (2012) Digital schools: how technology can transform education. Brookings Institution Press

Yang J, Tlili A, Huang R, Zhuang R, Bhagat KK (2021) Development and validation of a digital learning competence scale: a comprehensive review. Sustainability 13:5593

Yaron D, Karabinos M, Lange D, Greeno JG, Leinhardt G (2010) The ChemCollective – virtual labs for introductory chemistry courses. Science 328:584–58

Zheng B, Warschauer M, Lin CH, Chang C (2016) Learning in one-to-one laptop environments: a meta-analysis and research synthesis. Rev Educ Res 86:1052–1084

Acknowledgements
Supported by Johannes Kepler Open Access Publishing Fund and the federal state of Upper Austria.

Author contributions
AB: Conceptualization, Writing - original draft, Writing - review & editing; MM, RW, SS, FM: Writing - original draft, Writing - review & editing, ZS, AŠ, AŠ, LR, JV:Writing - review & editing, Validation.

Competing interests
The authors declare no competing interests.

Ethical approval
This study was conducted in accordance with the principles of the Declaration of Helsinki (1964) and its later amendments. Prior to the commencement of the research, the study protocol was reviewed by the Institutional Review Board of the Faculty of Education, University of Novi Sad (Approval Code: 06-22-6/23; Approval Date: December 11, 2023). Given the non-interventional and anonymous nature of the online questionnaire with adult participants and no collection of personal identifiers or sensitive data, the board granted an exemption/waiver of further formal approval. Data collection and storage were conducted under local ethical oversight in Serbia, thereby fulfilling the requirement for prior review by a responsible local ethics committee in line with Article 23(3) of the Declaration of Helsinki.

Informed consent
Children and minors were not included as participants in this study. Prior to completing the anonymous questionnaire, all potential participants received written information at the beginning of the survey, clearly explaining the purpose, objectives, procedures, and intended use of the data. Participants were explicitly informed that their participation was voluntary, that their anonymity was guaranteed, and that they had the right to withdraw at any time without providing a reason and without any negative consequences. Written electronic informed consent was obtained between 10 May and 28 June 2024, when participants voluntarily proceeded to complete the questionnaire. By doing so, participants agreed to the use of their de-identified data solely for academic research and publication in aggregated form. All responses were collected anonymously and treated as strictly confidential.

Additional information
Correspondence and requests for materials should be addressed to Branko Anđić.

Reprints and permission information is available at http://www.nature.com/reprints

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.