

Perceived utility moderates motivational intervention effects in learning to teach responsibly with GenAI

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ABSTRACT

Making responsible decisions when integrating artificial intelligence (AI) into teaching requires educators to simultaneously consider technological, pedagogical, and ethical knowledge. However, pre-service teachers often lack this integrated understanding, limiting their ability to reason responsibly in AI-supported educational contexts. Prior research has shown that motivational interventions, particularly those enhancing the utility-value of learning content, can support knowledge integration processes during learning. However, their potential effects on knowledge acquisition remain limited. In this experimental field study ($N = 158$), we investigated the effects of a scaffolded utility-value intervention on pre-service teachers' knowledge integration and knowledge acquisition. Additionally, we explored potential aptitude-treatment interaction effects, as utility-value interventions are regarded as especially beneficial for learners with initial low perceived utility-value. Using a one-factorial experimental design with three conditions, participants were assigned to either a utility-value intervention without scaffolds, a scaffolded utility-value intervention, or a control condition before engaging with a digital learning environment that addressed technical, pedagogical, and ethical issues related to AI use in teaching. Overall, the analyses revealed no general effects of the interventions. However, exploratory moderation analyses suggested that the utility-value intervention was detrimental to the knowledge integration of pre-service teachers with high initial perceived utility-value. These findings highlight the importance of tailoring motivational support to learners' individual prerequisites to foster the development of professional knowledge for the responsible integration of AI in teaching.

Generative artificial intelligence (GenAI) is increasingly shaping educational contexts, holding potential for formative assessment, personalized feedback, and adaptive learning systems [1,2]. At the same time, GenAI's probabilistic outputs can reproduce societal biases, spread misinformation, and compromise privacy in ways that are difficult to detect and control [1,3]. GenAI is not a neutral medium but a socio-technical system, amplifying the need for ethical reflection in education [4].

Therefore, GenAI is creating new demands for teacher education as (future) teachers are expected to not only understand the technological functions (technological knowledge: TK) of AI but also to reflect on ethical implications (ethical knowledge: EK) within pedagogical contexts (pedagogical knowledge: PK) to navigate responsible AI-enhanced teaching [5,6].

The TPACK framework [7] provides a foundation for conceptualizing professional knowledge for technology-enhanced teaching, while the

concept of knowledge integration [8] specifies the cognitive process through which TK, EK, and PK knowledge domains become meaningfully connected to form coherent professional understanding. In line with recent AI-specific extensions of TPACK, such as Intelligent-TPACK [9], this integrative process becomes particularly salient when teachers work with AI-based technologies that require technological and ethical reasoning to be coordinated within pedagogical contexts. Through this knowledge integration process, fragmented domain-specific knowledge (e.g., understanding AI functions, ethical implications, or pedagogical strategies) becomes integrated knowledge, enabling teachers to reason and act flexibly and responsibly in GenAI-supported classrooms.

Thus, knowledge integration represents the underlying cognitive mechanism by which pre-service teachers develop TPACK as a form of professional knowledge. Such integration is particularly demanding for pre-service teachers, whose professional knowledge is often fragmented and lacks coherence across domains [10,11]. Despite its relevance,

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instructional strategies to support knowledge integration remain underexplored. Generic studies indicate that enhancing pre-service teachers' utility-value through instructional support fosters knowledge integration [11–13] and, therefore, facilitates the cognitive effort required for integrating TK, EK, and PK. Hence, increasing pre-service teachers' perceived utility-value may serve as a motivational scaffold that supports the development of integrated professional knowledge within the TPACK framework. Therefore, in our approach, we enhance value alignment by guiding self-referential tasks with prompts tailored to pre-service teachers' future profession [11] and by reducing cognitive load through task segmentation [14]. However, the effectiveness of utility-value interventions may depend on motivational prerequisites. If pre-service teachers already perceive GenAI-TPACK as valuable for their teaching, additional scaffolds may be redundant [15].

To address these issues, we adopted a twofold approach by simultaneously testing the effectiveness of the interventions and accounting for individual motivational prerequisites.

We conducted a field experiment with pre-service teachers, randomly assigning them to one of three conditions (utility-value intervention without scaffolds, utility-value intervention with scaffolds, or control condition) before engaging in a hypertext learning environment on GenAI-TPACK. We analyzed pre-service teachers' knowledge integration, perceived utility-value, and how the initial perceived utility-value moderated the effectiveness of the intervention.

Theoretical background

Knowledge domains of GenAI-TPACK

As AI gained widespread attention within education, the well-established TPACK framework [7], which conceptualizes the interplay between TK, PK, and content knowledge (CK) in teaching with technology, has been adapted to the affordances of AI. Recent models, such as AI-TPACK and Intelligent-TPACK (e.g., [9,16]), have incorporated AI-related professional knowledge. The Intelligent-TPACK model [9] conceptualizes teachers' professional knowledge across three domains: technological TK, PK, and CK, wherefore technological knowledge, in this case, refers to AI-based technologies (see Fig. 1). Celik [9] emphasized that ethical awareness is essential when teaching with AI, given the socio-technical implications of automated feedback, data-driven decisions, and algorithmic bias, and demonstrated that ethical knowledge has a positive influence on TPK, TCK, and ultimately, TPACK itself, highlighting the interconnectedness of TK and EK. Similarly, Deng and Zhang [17] have emphasized the need to embed ethics systematically within pre-service teachers' assessment of TPACK and have developed a validated assessment instrument by implementing ethical knowledge as a separate knowledge domain (EK) alongside TK, PK, and CK. In general,

although ethical reasoning is integral to responsible teaching with GenAI, ethics remains underrepresented in TPACK research, despite these advances.

Beyond modeling teachers' professional knowledge, Heath and Moore [18] argue for conceptualizing ethics not as a static body of norms but as a dynamic „reflective loop that is integrated into decision making and practice“, wherefore „professional ethics can become a form of reflection-in-action“ ([18], p. 5). This perspective suggests that ethical reasoning should be interwoven with teaching practice, particularly when navigating the uncertainties and societal implications of cross-sectional AI technologies and complements a transformative view of TPACK [19]. Thus, we propose that AI-related professional knowledge must include ethics as an integral cross-cutting dimension, interfacing with TK, PK, and CK.

Bridging TK, EK, and PK: defining GenAI-TPEK

In specifying our approach for this study, we exclude CK, as the study was conducted within the context of pre-service teacher education in a cross-curricular lecture on digital teaching and learning, which was not subject-specific. Building on prior extensions such as Intelligent-TPACK [9] and GenAI-TPACK [20], our framework advances this line of research by conceptualizing EK as a distinct and coequal domain alongside TK about GenAI and PK. Because ethical reasoning in AI-supported teaching requires distinct epistemic structures, as it involves principles of fairness, accountability, and transparency that cannot be derived from technological or pedagogical reasoning, we argue that treating ethics as a distinct knowledge domain is theoretically indispensable. As pre-service teachers must actively connect ethical reflection with technological understanding and pedagogical judgment rather than applying ethics post hoc as an evaluative filter, GenAI-TPEK does not merely add ethics to TPACK but redefines the interdependence of professional knowledge domains. This conceptualization makes it possible to empirically investigate how teachers integrate these distinct forms of reasoning when learning to teach responsibly with GenAI. Based on this conceptualization, we refer to this generic knowledge facet of the TPACK framework as GenAI-TPEK (see Fig. 1) throughout this paper.

Although each of the knowledge domains represents distinct, domain-specific knowledge needed for the successful implementation of technology in teaching, effective technology integration in teaching requires more than expertise in isolated knowledge domains [16]. Instead, the capacity to interweave these domains within the process of knowledge integration is integral.

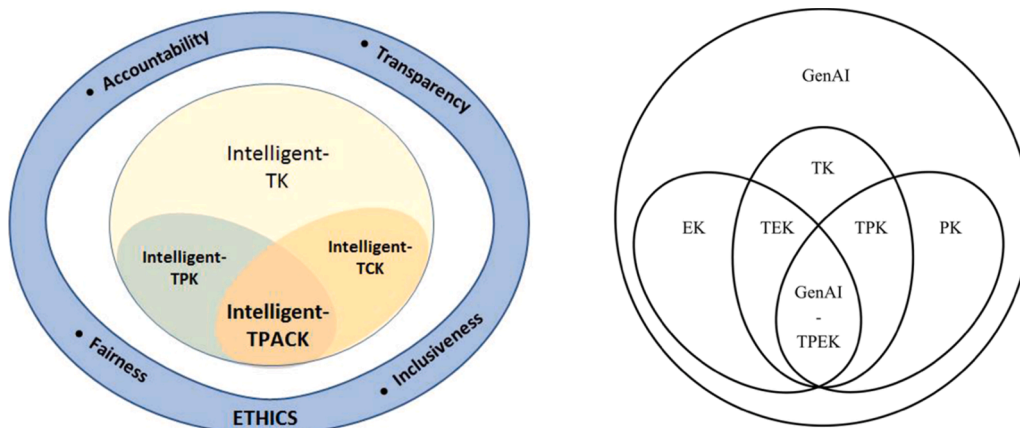


Fig. 1. Intelligent-TPACK Framework Compared to the GenAI-TPEK Framework.

Underlying processes of acquiring GenAI-TPEK

We conceptualize knowledge integration as a cognitive process in which humans (e.g., pre-service teachers) blend and connect originally conceptual-disjunct knowledge facets (e.g., TK, EK, PK) via assimilation and accommodation to form new chunks of knowledge (see [21]). We consider such knowledge integration processes as an important underlying cognitive process to transform formerly isolated knowledge structures to new knowledge structures that inform instructional planning, implementation, and the reflection in GenAI-supported teaching, ultimately developing transformative cognitive structures that support flexible teaching decisions in novel situations [8,19]. For instance, teachers may connect technological background knowledge (e.g., of machine learning processes) to ethical implications (e.g., algorithmic bias) within pedagogical contexts (e.g., grading processes). Rather than treating these components in isolation, this process involves creating integrated knowledge structures that transform by enabling flexible application across various teaching contexts [8]. From this perspective, our study addresses the processual level by iteratively refining the integration of domain-specific knowledge of TK, EK, and PK related to GenAI.

Motivational and cognitive learner characteristics for acquiring GenAI-TPEK

As expertise research has shown, performing knowledge integration is a demanding task [11], but also critical for teaching expertise [11,22]. These challenges are particularly relevant to pre-service teachers, who often lack both teaching experience and technological as well as ethical expertise. In contrast, in-service teachers, drawing on their professional experience, tend to organize their knowledge in a more coherent and integrated manner. In comparison, pre-service teachers' knowledge remains largely fragmented across distinct, domain-specific components [10,22], making it difficult for them to understand why and how knowledge domains should be connected [23].

Therefore, knowledge is not enough. The importance of taking value beliefs within pre-service teachers' professional development into account is highlighted in the study by Cheng and Xie [24], which examined value beliefs in (non) intervention studies focusing on teachers' TPACK. They found that value beliefs significantly predicted TPACK and that value beliefs had positive effects on TPACK. Therefore, providing motivational support by targeting pre-service teachers' values seems promising for improving task performance in terms of fostering TPACK-related knowledge integration within pre-service teachers' professional development. Furthermore, several studies have emphasized the critical role of teacher motivation, particularly utility-value, in the effective integration of utility-value interventions [12,25]. For instance, Backfisch et al. [12] demonstrated that utility-value interventions improved pre-service teachers' knowledge integration during processing online learning environments. Fütterer, Backfisch, et al. [25] found that teachers' perceived utility-value was crucial for the quality of technology integration within teaching. Additionally, Fütterer, Richter, et al. [26] identified teacher motivation as a significant predictor of engagement in online professional development courses.

Against this background, we provided pre-service teachers with motivational support in our instructional design, specifically aimed at fostering the integration of AI-related technological knowledge with pedagogical strategies and ethical considerations.

Motivational support: enhancing pre-service teachers' utility-value

According to expectancy-value theory [27], learners are more likely to engage deeply with the learning content when they perceive it as valuable for their personal or professional goals. A key construct within this theory is utility-value, which refers to the perception that a learning task is useful. Within this framework, utility-value refers to the

perceived relevance of a task in relation to one's personal goals or broader societal contributions, thereby enhancing interest and performance in the task [28–31]. In the context of GenAI-TPEK, this perspective is particularly important because the ethical and societal dimensions of AI, such as privacy, bias, and hallucination, are not established parts of pre-service teachers' study programs in Germany, which focus mainly on content and pedagogical knowledge. At the same time, the socio-technical nature of AI entails far-reaching social and ethical consequences, which become especially salient in the highly social context of education. Future teachers thus face the professional responsibility of critically reflecting on AI use in education, not only to TK, PK, and EK, but also to prepare their students for responsible participation in a society increasingly shaped by AI. TK, as well as EK, therefore, constitutes an additional area of expertise that must be acquired. Without explicitly demonstrating utility-value through motivational support, these knowledge domains risk being perceived as peripheral or overly abstract. By linking these GenAI-specific dimensions to teachers' educational responsibilities, we emphasize their utility and provide pre-service teachers with the necessary motivation to actively address these challenges. This engagement establishes consistency with pedagogical responsibility and strengthens the conceptual justification for implementing utility-value interventions as motivational support in the learning process of GenAI-TPEK. Increasing the perceived utility-value of AI-related technological and ethical knowledge can thus help pre-service teachers realize its relevance to their future profession within pedagogical decision-making, fostering greater engagement and deeper conceptual understanding. Therefore, supporting pre-service teachers to recognize the value of technological and ethical knowledge within pedagogical contexts is essential [32]. The motivational effects of utility-value are reflected in learners' cognitive engagement. As Eccles and Wigfield [27] state, with an increased utility-value, learners are more likely to invest greater cognitive resources, which, according to Hulleman and Harackiewicz [33], leads to deeper cognitive processing and greater elaboration. Building on this perspective, utility-value interventions are not assumed to exert their influence on knowledge integration directly but rather through their effects on learners' engagement and cognitive processing. Expectancy-value theory [27] suggests that when pre-service teachers perceive learning content as useful, they are more likely to invest effort and persist in demanding tasks. In the context of GenAI-TPEK, such cognitive engagement is essential for linking TK, PK, and EK into coherent professional knowledge structures. From this perspective, utility-value interventions function as motivational scaffolds that create the motivational and cognitive preconditions for knowledge integration [8,34].

Building upon this theoretical foundation, Kale [35] called for more targeted interventions that explicitly promote the perceived utility-value of technology integration in teacher education. Addressing this need, Backfisch et al. [12] implemented a utility-value intervention in an experimental design within two studies. The authors investigated pre-service teachers' TPACK knowledge integration by implementing a utility-value intervention in a two-group design with an experimental condition with a utility-value intervention and a control condition. There were no significant effects of the intervention on knowledge acquisition or perceived utility-value found. However, analyses of navigation behavior within the learning environment indicated that pre-service teachers in the utility-value condition were more likely to integrate knowledge across different domains compared to the control condition. We adapted the approach of Backfisch et al. [12] to GenAI-TPEK. In the context of our study, we aimed to enhance pre-service teachers' perceived utility-value of engaging with ethical considerations by explicitly linking technological knowledge of AI to ethical implications in pedagogical contexts within a utility-value intervention. This approach aims to increase pre-service teachers' awareness of the ethical implications of AI and reason with technological background knowledge.

We implemented a utility-value intervention in a preceding study [36], which served as the conceptual and methodological foundation for the present study. In our previous study, pre-service teachers ($N = 274$) engaged with a hyper-text learning environment on AI's technological and ethical aspects. Additionally, we provided them with different instructional support via a 2×2 -factorial design crossing the factors utility intervention [yes, no] and worked examples [yes, no]. We found that worked examples providing a step-by-step demonstration on how to integrate TK, EK, and PK support enhanced acquisition of domain-specific and integrated knowledge, whereas motivational support in the form of a utility-value intervention did not. To ensure methodological consistency, worked examples were again implemented in the present study as an instructional support factor. Given their demonstrated effectiveness, they were held constant across all conditions, allowing potential differences in outcomes to be attributed to the utility-value manipulations rather than to variations in instructional guidance. The worked example was presented after the hypertext learning environment but before the open-ended knowledge integration task. By maintaining comparability with our previous design, we ensured that any observed effects could be attributed to refinements of the utility-value intervention rather than to changes in baseline instructional support. However, exploratory analysis revealed that deeper processing during the utility-value intervention led to higher performance on knowledge integration.

Building on these findings, in this study, we developed a scaffolded utility-value intervention designed to reduce cognitive overload, enabling all pre-service teachers to process the utility-value intervention accurately, and added pedagogical knowledge as a third knowledge domain. As suggested by Hulleman and Harackiewicz [37], we aimed to implement scaffolding mechanisms that guide pre-service teachers through the process of reflecting on utility-value in relation to personal goals. Scaffolding strategies have been shown to foster meaningful engagement with value-related prompts by providing structure, feedback, or prompts that encourage elaboration [34,38]. For example, structured reflection prompts or example responses can help learners generate more personally relevant utility statements, which in turn increases the effectiveness of the intervention by enhancing personal value and a self-referential statement tailored to pre-service teachers' future teaching, supported by task-segmentation [14]. By integrating such scaffolding mechanisms into our instructional design, we seek to ensure that all pre-service teachers, not only those who spontaneously engage deeply with the content, can benefit from the utility-value intervention. Instructing learners with different scaffolds just-in-time aligns with perspectives from instructional design research [39], which emphasize that scaffolds are most effective when provided at different stages of learning in line with the requirements of a learning task. Accordingly, our focus was not on isolating the effects of each component, but on testing whether scaffolding mechanisms in general enhance the benefits of the utility-value intervention.

Fig. 2 provides an overview of the theoretical framework, summarizing the core constructs and depicting how motivational and cognitive mechanisms interact in fostering integrated knowledge in the form of GenAI-TPEK.

Research questions and hypotheses

In the present preregistered (see <https://aspredicted.org/zrs6-9y5b.pdf>) study, we aimed to refine the utility-value intervention from our previous study [36] to reduce cognitive overload and promote germane cognitive processing by scaffolding the task. To provide a meaningful context for the intervention, pre-service teachers first viewed an expert video statement highlighting the interdependency of technological and ethical knowledge. The video was followed by a self-referential writing task, encouraging pre-service teachers to relate the video content to their future professional practice. To support deep engagement, the writing task was segmented into smaller, manageable chunks, fostering structured processing [14]. In line with the previous reasoning, we hypothesized:

Hypothesis 1 (H_1): General Effect of Utility-Value Interventions.

Pre-service teachers who receive a utility-value intervention (with and without scaffolds) demonstrate higher performance on knowledge posttests and higher scores in perceived utility-value compared to the control group.

Hypothesis 2 (H_2): Effect of Scaffolding Utility-Value Intervention.

Pre-service teachers who receive a scaffolded utility-value intervention demonstrate higher performance on knowledge posttests and higher scores in perceived utility-value compared to those who receive a utility-value intervention without scaffolding.

Exploratory Analyses on Aptitude-Treatment Interaction. As generic studies on utility-value showed the effectiveness of utility-value interventions, learners with initial motivational boundaries benefited the most, especially with self-generating tasks [33,40]. Therefore, in addition to investigating the effect of the intervention, individual differences should also be considered. Drawing on aptitude-treatment interaction [41], we explored whether pre-service teachers' initial perceived utility-value moderates the effect of the utility intervention on posttest knowledge integration. The aptitude-treatment interaction framework posits that instructional effectiveness depends on how well a treatment aligns with learners' prerequisites. In our case, pre-service teachers with low initial perceived utility-value may benefit from the intervention, while those with high initial perceived utility-value may experience redundancy [15]. Reinforcing utility-value through an intervention with already high initial perceived utility-value could lead to a cognitive trade-off, ultimately hindering the intervention's effectiveness.

Method

Participants and design

Our experimental study was embedded as a self-learning task within a lecture on teaching and learning with digital media in the Master of Education program of a German university. The study was implemented into the existing curriculum and tailored to address the specific needs and professional development goals of pre-service teachers. As preregistered, pre-service teachers who failed the attention checks ($n = 15$) were excluded, resulting in a final sample size of $N = 158$ pre-service teachers (68 % female, $M_{age} = 24.47$, $SD_{age} = 2.11$, $M_{semester} = 9.46$, $SD_{semester} = 3.38$, see details in Table 2). As we implemented our study in an authentic teacher education lecture, our sample size was determined by the number of lecture participants and exceeded the required sample size calculated in our pre-registered a priori power analysis with medium effects ($f = 0.25$), consistent with meta-analytic findings [14,42],

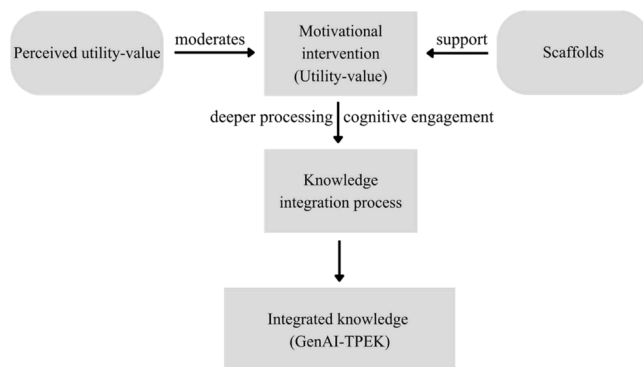


Fig. 2. Conceptual Model of the Core Constructs Underlying GenAI-TPEK Integration.

given a power of $\beta = 0.80$ and $\alpha = 0.05$ (G*Power 3.1: [43]).

We employed a one-factorial pre-posttest experimental design with three conditions. Pre-service teachers were randomly assigned to one of two experimental conditions (utility-value intervention without scaffolding or utility-value intervention with scaffolding) or a control condition without any intervention.

Materials

Materials were implemented within an online questionnaire using SoSci Survey, version 3.7.06 [44].

Online learning environment

All pre-service teachers accessed an online hypertext learning environment that facilitated self-regulated learning of the technological, ethical, and pedagogical dimensions of AI. The main page featured a navigation menu that linked the interconnected TK, EK, and PK domains, organized by four different chapters. Each chapter (e.g., algorithmic bias in AI-supported scoring processes) included three subchapters: Technological aspects (e.g., training data in machine learning), ethical implications (e.g., bias and discrimination), and pedagogical contexts (e.g., the scoring process). These subchapters were designed to complement one another, forming an integrated and cohesive body of knowledge bridging all three domains.

At the end of the learning environment, all pre-service teachers were presented with a worked example. The worked example provided a step-by-step demonstration of how to integrate knowledge across domains to support the successful solution of the knowledge integration task during the posttest (see Boos et al., [36]).

Motivational support (Utility-Value intervention)

Utility-Value Intervention without Scaffolds (UV Condition). We implemented a video featuring expert statements (see Fig. 3) that highlighted the utility of combining technological and ethical knowledge for future professional practice [12,45].

After watching the video, pre-service teachers were asked to write a self-referential statement [12,46] reflecting on the connections between technological and ethical aspects in the video and pre-service teachers' personal lives, as shown in Fig. 4.

Utility-Value Intervention with Scaffolds (UVS Condition). In contrast to the UV condition, the UVS condition incorporated targeted

scaffolding elements designed to deepen pre-service teachers' engagement with the video content. First, the video, which was the same as in the UV condition, included a prompt instructing pre-service teachers to actively consider how the discussed technological and ethical arguments relate to their personal lives and profession:

While watching the video, reflect on why the aspects mentioned are relevant to your personal life and how you can relate the content to your own experiences. Observe the interplay between technological and ethical dimensions. You will be required to identify and articulate such connections at a later stage.

Second, the subsequent self-referential writing task was broken down into structured sub-prompts designed to scaffold pre-service teachers' reflections. These sub-prompts guided pre-service teachers in aligning the extrinsically presented value of the intervention with their personal and professional futures (see Fig. 5).

Measures

Domain-Specific Knowledge (Pre- and Posttest). The domain-specific knowledge of pre-service teachers was assessed through pre- and posttests. Each chapter of the learning environment was represented by four multiple-choice questions that addressed the three knowledge domains (e.g., TK: "Which statements of algorithms are correct?", EK: "Which statements about discrimination are correct?", PK: Which statements about objectivity in educational contexts are correct?"). The questionnaire included four multiple-choice questions related to TK, four related to EK, and four related to PK, resulting in a total of 12 questions. If the answer pattern of each question was correct, pre-service teachers received one point per question, resulting in a maximum score of 12 points.

The internal consistency of our self-developed items for assessing domain-specific knowledge in the pre- and posttests was evaluated using the greatest lower bound (GLB), which accounts for multidimensionality in the data [47]. GLB of domain-specific knowledge was sufficient (GLB = 0.76).

Integrated Knowledge (Posttest). We assessed pre-service teachers' integrated knowledge with four open-ended questions, each corresponding to a chapter in the learning environment (GLB = 0.99). The open-ended questions presented real-world challenges within the educational context through problem-based vignettes that combined technological knowledge with ethical considerations in a pedagogical



Fig. 3. Video Expert Statement within the Utility-Value Intervention.

Note. The screenshot was translated from German to English and represents an expert in technological knowledge. The expert in ethical knowledge was similarly portrayed. At the end of the video, both experts engaged in a dialogue, emphasizing the importance of integrating knowledge from both domains.

Why does knowledge about AI matter?**Please answer in complete sentences.**

Which aspects of the video are personally relevant or useful in your (future) life? Please give reasons for your answer and give examples that are as concrete as possible.

Fig. 4. Self-referential Writing Task of the UV Condition.

Note. The text was translated from German into English.

Why does knowledge about AI matter?**Please answer in complete sentences.**

Examine the significance of the video's content for the education system and schools as institutions. Why is this topic relevant from a societal or educational policy perspective? What opportunities or risks does it present for the future development of schools and teaching, and how does it relate to current debates in education?

As a future teacher, reflect on your reaction to the statements in the video. Which statements convinced you, shifted your perspective, or prompted you to question your assumptions?

Think about how you would implement the content of the video in your future lessons or everyday school life. Provide concrete examples.

Fig. 5. Self-Referential Writing Task of the UVS Condition.

Note. The text was translated from German into English.

context. An example reads like the following:

Mr. Matwo teaches a diverse group of students. To reduce his workload, he uses an AI-based assessment system to analyze and grade student work. After a few weeks of using the AI assessment application, Mr. Matwo notices that certain groups of students consistently receive lower grades than others. On closer analysis, he finds that the AI-based assessment system tends to disadvantage students whose first language is not German, as well as girls. Why might these problems arise, and how could they be solved (in the future)? Explain your answer, taking into account both the technological functionality and the ethical challenges. Conclude responsible pedagogical practice.

To answer these questions, pre-service teachers were required to apply integrated knowledge by drawing on their technological understanding and ethical reasoning to analyze each vignette within a pedagogical context. Pre-service teachers could yield a maximum of four points for each open question, resulting in a total score of 16 points. Up

to three points were allocated based on the extent to which the response demonstrated an integrated application of TK, EK, and PK. An additional point was added for the contextually appropriate transfer of the GenAI-TPEK to concrete examples within educational practice. To ensure the reliability of coding the open-ended questions, 20 % of the responses were coded by two independent raters, yielding an excellent inter-rater reliability $ICC_{2,1} \geq 0.92$ [48].

Perceived Utility-value (Pre- and Posttest). Perceived utility-value based on Eccles and Wigfield [27] was assessed for integrating technological and ethical knowledge with four items (e.g., "I believe that it is necessary to link the technological functioning and ethical challenges of artificial intelligence.") on a four-point Likert scale ranging from "strongly disagree" to "strongly agree" (Cronbach's $\alpha > 0.75$).

Procedure

After completing the pretest and demographics questionnaire (see variables in Table 3), pre-service teachers were randomly assigned to one of the three conditions. They either watched a randomly assigned utility-value intervention video and received a writing task with or without scaffolds, or were directly forwarded to the learning environment. After completing the learning environment within a self-selected timeframe and a self-selected processing sequence, all pre-service teachers completed the posttest, including domain-specific and integrated knowledge tests. The study lasted approximately 45 min. Pre-service teachers received a monetary incentive of 7 euros for their participation in the study.

Data analysis

To test our hypotheses, we conducted planned contrast analyses [49] within an ANCOVA framework. The contrasts were specified and tested sequentially for each hypothesis. As independent variables, we used planned contrasts to compare (H_1) the experimental utility-value conditions (UV and UVS) with the control condition, and (H_2) the scaffolded (UVS) with the non-scaffolded utility-value intervention (UV). For both hypotheses, we set (a) domain-specific knowledge or knowledge integration as the dependent variable, controlling for prior knowledge, and (b) perceived utility-value as the dependent variable, controlling for the initial perceived utility-value. To explore potential individual differences in terms of aptitude-treatment interaction, we performed moderation analysis using the contrast-coded conditions of H_1 to investigate the potential moderating effect of initial perceived utility-value on knowledge integration. To probe the moderation effect, we applied a Johnson-Neyman analysis to identify the range of the moderator for which the intervention's effect was statistically significant.

As an effect size measure, we used partial η^2 (η_p^2), interpreting values $\eta_p^2 < 0.06$ as a small effect, values $0.06 \leq \eta_p^2 \leq 0.14$ as a medium effect, and values $\eta_p^2 > 0.14$ as a large effect [50]. We performed all statistical analyses using R [51] in RStudio version 4.3.3 [52].

Results

Preliminary analyses

Attention Checks. To enhance implementation fidelity and ensure data quality, pre-service teachers who failed predefined attention check items were excluded from the analysis. After applying these criteria, $N = 158$ out of the original 173 datasets remained for further analysis.

Outlier Analyses. To identify potential outliers in the dependent variable (posttest scores), boxplot analyses were conducted separately for each experimental condition (UV, UVS, and control). Visual inspection of the box plots revealed a small number of data points outside the whisker range in all groups. However, automated detection using the `boxplot.stats` function [51] indicated no statistical outliers across conditions. All participants were therefore included in the main analyses.

Randomization Check and Baseline Comparison. To ensure the comparability of groups at baseline, the initial prerequisites of pre-service teachers were examined. No significant differences were found between conditions in their pretest measures (see Table 4 for descriptive and statistical values).

Implementation fidelity. To assess levels of response quality of the writing tasks within the experimental conditions UV and UVS ($n = 102$), we employed a self-developed coding scheme with indicators adapted from Brisson et al. [53]. According to this scheme, a total score was calculated by cumulating the score of relevance arguments, personal references, and the degree of reflection. To ensure the reliability of coding for the open-ended questions, 20 % of the responses were independently coded by two raters. We yielded excellent inter-rater reliability, as indicated by an intraclass correlation coefficient of $ICC_{2,1}$

$\geq .91$ [48]. Descriptive analysis revealed that pre-service teachers in the scaffolding condition ($n = 47$) achieved substantially higher integration scores ($M = 10.96$, $SD = 4.27$) compared to those in the condition without scaffolding ($n = 55$; $M = 5.60$, $SD = 3.27$), indicating an advantage of scaffolding for performing the writing task.

Furthermore, we explored task engagement with the writing-task scores serving as a proxy for engagement. To investigate whether engagement influenced the intervention's effects, we conducted a multiple linear regression analysis with experimental condition (UV vs. UVS) and writing-task scores as predictors of knowledge integration at posttest. The control group was excluded from this analysis, as no intervention was applied.

There was a significant main effect of the writing-task score on knowledge integration, $b = 0.38$, $SE = 0.12$, $t(93) = 3.14$, $p = .002$, $\eta^2 = 0.20$, indicating that higher scores within the writing task of the utility-value intervention (independent of condition UV or UVS) were associated with higher posttest performance regarding knowledge integration after the intervention.

Main analyses

Hypothesis 1 (H_1): general effect of utility-value intervention

We examined the general effect of the utility-value interventions (UV- and UVS-conditions) across three outcome measures: domain-specific knowledge (domain-specific multiple-choice questions in the knowledge posttest, controlling for prior knowledge), integrated knowledge (integrated knowledge with open-ended questions in the posttest, controlling for prior knowledge), and perceived utility-value (post-intervention, controlling for baseline levels). Contrast weights were set to compare both UV conditions (UVS and UV) against the control group (UVS = +0.5, UV = +0.5, Control = -1).

Domain-Specific Knowledge. The effect of the utility-value intervention on domain-specific learning outcomes, controlling for prior knowledge, was not statistically significant ($p = .408$, see detailed results in Table 1), indicating no general effect of the intervention regarding domain-specific knowledge. Prior knowledge was a significant predictor ($p < .001$, see detailed results in Table 1).

Integrated Knowledge. The model predicting learning outcome regarding integrated knowledge was not significant ($p = .533$, see detailed results in Table 1), indicating no general effect of the intervention regarding integrated knowledge. Prior knowledge was a significant predictor ($p < .001$, see detailed results in Table 1).

Perceived Utility-value. The regression model for post-intervention perceived utility-value (controlling for baseline levels) per condition was not significant ($p = .231$, see detailed results in Table 1). Initial perceived utility-value was a significant predictor of post-intervention perceived utility-value ($p < .001$, see detailed results in Table 1).

Hypothesis 2 (H_2): effect of scaffolding the utility-value intervention

To test Hypothesis 2, we conducted contrast analyses comparing the segmented utility-value condition (UVS) to the non-segmented condition (UV), using contrast weights (UVS = +1, UV = -1, Control = 0). This contrast was applied to three outcomes: domain-specific knowledge (domain-specific multiple-choice questions in the posttest, controlling for prior knowledge), integrated knowledge (open-ended integration items), and perceived utility-value (post-intervention, controlling for initial perceived utility-value).

Domain-Specific Knowledge. The effect of segmenting within the utility-value intervention on domain-specific learning outcomes, controlling for prior knowledge, was not statistically significant ($p = .191$, see detailed results in Table 1), indicating no effect of segmenting the intervention regarding domain-specific knowledge. Prior knowledge was a significant predictor ($p < .001$, see detailed results in Table 1).

Integrated Knowledge. The model predicting learning outcome

Table 1
Linear Regression Results Testing H₁ (UV/UVS vs. Control) and H₂ (UVS vs. UV).

Hypothesis	Outcome	Predictor	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>	η_p^2
H ₁	Domain-specific knowledge	UV/UVS vs. Control	0.17	0.21	0.83	.408	-
		Prior knowledge	0.65	0.07	9.31	< 0.001***	.36
	Integrated knowledge	UV/UVS vs. control	-0.26	0.42	-0.63	.533	-
		Prior knowledge	0.55	0.14	3.93	< 0.001***	.09
	Perceived utility-value	UV/UVS vs. control	0.05	0.04	1.20	0.231	-
		Initial perceived utility-value	0.44	0.06	7.86	< 0.001***	.29
H ₂	Domain-specific knowledge	UVS vs. UV	-0.25	0.19	-1.32	.191	-
		Prior knowledge	0.65	0.07	9.31	< 0.001***	.36
	Integrated knowledge	UVS vs. UV	-0.20	0.38	-0.53	.600	-
		Prior knowledge	0.55	0.14	3.93	< 0.001***	.09
	Perceived utility-value	UVS vs. UV	0.023	0.034	0.68	.500	-
		Initial perceived utility-value	0.444	0.06	7.86	< 0.001***	.29

*** $p < .001$.

regarding integrated knowledge was not significant ($p = .600$, see detailed results in Table 1), indicating no effect of segmenting regarding integrated knowledge. Prior knowledge was a significant predictor ($p < .001$, see detailed results in Table 1).

Perceived Utility-Value. The regression model for post-intervention perceived utility-value (controlling for baseline levels) per condition was not significant ($p = .500$, see detailed results in Table 1). Initial perceived utility-value was a significant predictor of posttest perceived utility-value ($p < .001$, see detailed results in Table 1).

Explorative analysis

In the next step, we explored potential inter-individual effects as outlined in our preregistration. In terms of aptitude-treatment interaction, the initial perceived utility-value of GenAI-TPEK represents a predispositional factor that may influence the extent to which individuals benefit from our intervention. Thus, we examined whether the interaction of initial perceived utility-value moderated the effectiveness of utility-value interventions (contrast-coded according to H₁) on pre-service teachers' knowledge acquisition. We conducted a linear regression analysis to investigate the effects of utility-value interventions (contrast-coded predictor), initial perceived utility-value, and their

interaction on knowledge integration (as measured at the posttest). There was a significant interaction between the experimental conditions receiving an utility-value intervention (UV and UVS) and the control condition, and initial perceived utility-value, $b = -1.84$, $SE = 0.88$, $t(148) = -2.11$, $p = .036$, $\eta_p^2 = 0.03$, indicating initial perceived utility-value moderated posttest knowledge integration performance depending on whether pre-service teachers were in the control or in one of the experimental conditions.

We further explored this interaction by visualizing the moderating role of initial perceived utility-value on posttest knowledge integration across conditions (see Fig. 6). The interaction plot revealed that the difference in posttest knowledge integration between the intervention (UV+UVS) and control condition was most pronounced at lower levels of initial perceived utility-value. In this range, participants in the intervention condition showed higher posttest performance compared to those in the control condition, suggesting that the intervention was particularly beneficial for learners with low initial perceived utility-value. In contrast, in the intervention condition (UV+UVS), posttest knowledge integration remained relatively stable across levels of initial perceived utility-value, with a slight downward trend with the increase of initial perceived utility-value.

By applying the Johnson-Neyman technique, we could confirm this reversal tendency, as we found a significant positive trend below initial

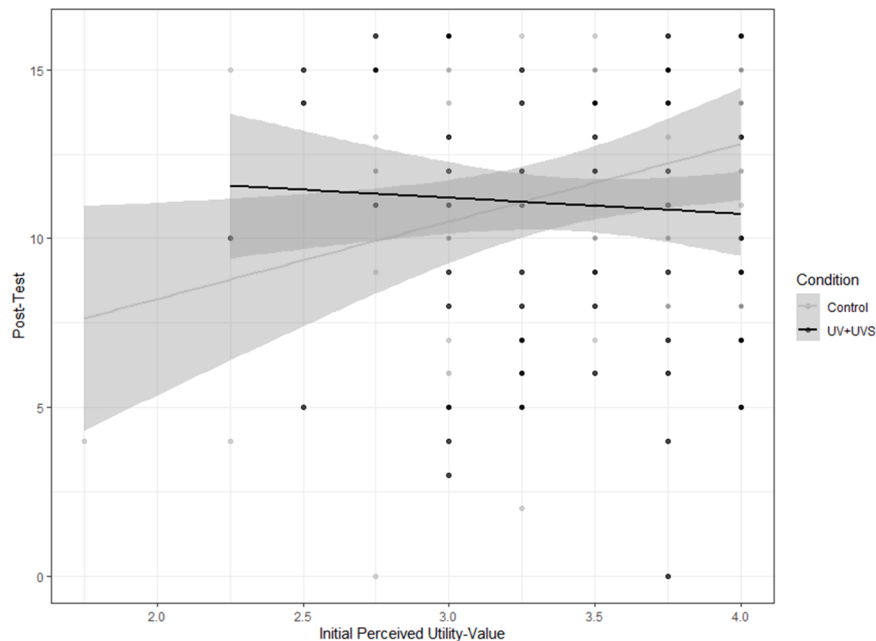


Fig. 6. Interaction Between Initial Perceived Utility-Value and Condition on Posttest Knowledge Integration.

Note. Each point represents an individual participant. Regression lines with 95 % confidence intervals illustrate the interaction pattern.

perceived utility-value of ~ 0.78 and a significant negative trend for initial perceived utility-value of ~ 4 .

Thus, while the utility-value intervention may tend to compensate for low initial perceived utility-value, utility-value interventions seem detrimental for pre-service teachers with high initial perceived utility-value. However, these findings must be interpreted with caution, as our data showed an overall bias towards high initial perceived utility-value ($M = 3.41$, $SD = 0.48$, range = 1.75–4.00; see details per condition in Table 4).

Discussion

In this study, we aimed to empirically examine whether utility-value interventions in general and scaffolding utility-value interventions enhance the integration of domain-specific knowledge facets compared to the respective control group. Contrary to our initial hypothesis, the results suggest that neither utility-value interventions in general nor scaffolding the intervention significantly increased the level of domain-specific knowledge, knowledge integration, and perceived utility-value at posttest. However, our findings contribute to a more differentiated understanding of GenAI-TPEK by clarifying the conditions under which motivational scaffolds foster, rather than constrain, knowledge integration. Within GenAI-TPEK, professional knowledge in AI-enhanced teaching arises from the dynamic integration of TK, EK, and PK, rather than from their isolated accumulation. The absence of general effects refines this assumption by indicating that motivational interventions such as utility-value interventions act as conditional support whose effectiveness depends on learners' initial perceived utility-value. Hence, motivational activation alone may be insufficient to promote integrative knowledge construction when initial perceived utility-value is already high or cognitive demands are misaligned with motivational states.

One reason for the absence of statistically significant main effects may be attributed to methodological and contextual factors. Our sample size, while sufficient to detect medium effects according to our a priori power analysis, may not have captured smaller effects, and the limited number of test items per knowledge domain may have reduced measurement sensitivity. In addition, theoretical considerations such as redundancy effects and the relatively short intervention time in an authentic lecture setting may have further constrained the observable impact of the intervention.

Exploratory moderation analyses, however, revealed a significant interaction between experimental condition and pre-service teachers' initial perceived utility-value on knowledge integration. The pattern of the plot suggests that the utility-value intervention benefits only pre-service teachers who initially perceived their utility-value as low. The findings can be contextualized by expectancy-value theory, which posits that increases in perceived task-value have the most motivational leverage when utility-value is initially low, offering learners „room to grow“ [27]. In reverse, for pre-service teachers who already perceived the content as highly useful at pretest, the pattern suggests that the utility-value intervention might have been redundant or even disruptive. However, the decrease in post-test scores for increasing initial perceived utility-value is very small and requires further investigation to obtain reliable results. Given the narrow empirical range of the Johnson-Neyman analysis and the overall high initial perceived utility-value in our sample, this negative trend should therefore be interpreted with caution.

Our sample, on average, reported high levels of initial perceived utility-value ($M = 3.41$, $SD = 0.48$, range = 1.75–4.00), indicating a bias towards high initial perceived utility-value. If initial perceived utility-value is already high, further prompts to reflect on usefulness may become redundant, offering little additional motivational gain and potentially disengaging learners. Thus, the redundancy effect, which is widely discussed in the context of instructional support [15], may also apply to motivational support. Research on utility-value interventions suggests that excessive or misaligned prompts can diminish

effectiveness, particularly when they do not align with learners' motivational needs [40]. Several studies have shown that utility-value interventions can have negative effects on learners who are already highly motivated, particularly when these interventions involve generative tasks rather than direct instruction, as was the case in our study [54]. Thus, the interplay between cognitive load and motivation implies a trade-off: increasing motivation with utility-value interventions must not overwhelm learners with unnecessary guidance. Beyond these empirical outcomes, this study advances the theoretical and methodological scope of TPACK research by introducing GenAI-TPEK as an expanded framework in which EK is conceptualized as a domain equal to TK and PK. Positioning ethics as an integral dimension rather than an external add-on reconceptualizes professional competence in teaching with AI as a process of value-sensitive knowledge integration. This perspective responds to recent calls for a more reflexive and ethically grounded understanding of AI literacy in education [4,18]. Unlike prior studies that predominantly assess TPACK through self-reports or static knowledge tests, our approach examines how such integrated knowledge structures emerge during learning. We designed a scaffolded instructional environment that operationalizes integration as a guided cognitive and motivational process, combining structured reflection with utility-value prompts to activate learners' perception of professional relevance. By embedding these scaffolds in AI-based case vignettes, we link the acquisition and application of GenAI-related knowledge within authentic pedagogical-ethical dilemmas. Through this design, the study not only specifies the mechanisms through which ethical and technological reasoning become interwoven but also demonstrates how instructional principles can translate abstract theoretical models of professional knowledge into empirically testable learning processes. Consequently, our findings extend existing theory by framing knowledge integration as a value-dependent cognitive process central to responsible AI-enhanced teaching.

Implications for educational practice

Overall, the findings underscore that utility-value interventions should not be implemented as a universal one-size-fits-all approach. Instead, motivational interventions must be adapted to learners' prerequisites, ensuring that motivational support does not negatively influence cognitive processing. Therefore, in educational practice, tailoring such motivational interventions becomes increasingly important; they may not universally benefit all learners and could even be harmful.

Apart from that, task engagement with the writing task of the utility-value intervention showed that, rather than the depth of value-alignment, the specific scaffolds of the intervention were critical for fostering knowledge integration. These findings may also stem from sufficient cognitive capacity and other impact factors on task engagement. In any case, these findings highlight the importance of supporting self-referential processing within utility-value interventions to maximize educational impact.

Limitations and future directions

By measuring knowledge integration, we captured only the end product of this process. Since no significant main effects were observed, it would be valuable for future research to investigate and measure the underlying cognitive processes of pre-service teachers during learning.

A further methodological limitation concerns the uniform provision of worked examples to all participants, which may have reduced sensitivity to detect motivational effects; therefore, it would be interesting to replicate our findings without providing worked examples to isolate instructional from motivational effects.

Moreover, the combined implementation of in-video guidance and segmented reflection tasks in this study precludes conclusions about the isolated effects of each scaffolding element. However, treating these

scaffolds as an integrated mechanism more accurately reflects the way instructional supports operate in authentic educational contexts. While this integrated implementation limits inferences about the relative contribution of each scaffold, it more accurately represents authentic instructional design, where scaffolding mechanisms act synergistically across phases of learning rather than as isolated elements.

As our experiment was implemented in a 45-min lecture, it had a relatively short duration, which limited the extent to which internal motivational changes could develop, thereby constraining the potential impact of the intervention. From a research perspective, there is a strong rationale for designing longitudinal studies that capture intraindividual changes in motivation and professional knowledge over time. To address this limitation, we recommend implementing utility-value interventions over a longer timeframe and at multiple points during instruction. For example, utility-enhancing activities could be systematically integrated into each session of a seminar designed to foster GenAI-TPEK in pre-service teacher education by highlighting and aligning the learning content with pre-service teachers' profession. This approach would facilitate the observation of intraindividual changes in both perceived utility-value and the integration of domain-specific knowledge over time, enabling a more precise view into the interplay of interventions and individual prerequisites.

Overall, our findings suggest that the effectiveness of utility-value interventions cannot be considered in isolation. Rather, such interventions must be understood as embedded within a complex interplay of motivational, cognitive, and situational factors. Addressing these multifaceted influences remains a key challenge for future research, which should aim to disentangle and more precisely measure their respective impacts on pre-service teachers' professional knowledge.

Although the present intervention was tailored to pre-service teachers in a teacher education setting, the general approach could be adapted and transferred to other educational and even non-educational contexts, as fostering AI literacy and raising awareness of ethical implications is increasingly relevant for all citizens. Beyond contextual transferability, our exploratory aptitude–treatment interaction findings highlight a more general principle: motivational interventions should be aligned with learners' prerequisites rather than implemented as one-size-fits-all. This perspective not only informs the design of adaptive interventions across diverse learning contexts but also opens up future directions for longitudinal research. In particular, examining intraindividual trajectories of perceived utility over time may provide a more precise understanding of how motivational support interacts with learning processes, given that cross-sectional comparisons between learners are limited and yielded no main effects in the present study.

Conclusion

This study demonstrates that scaffolding a utility-value intervention does not, in itself, lead to greater integration of domain-specific knowledge among pre-service teachers. However, the findings highlight the moderating role of initial perceived utility-value, suggesting that motivational prerequisites are critical for intervention effectiveness and add to a growing body of evidence that the impact of utility-value interventions is rather conditional than universal. Rather than applying a one-size-fits-all approach, motivational support should be aligned with pre-service teachers' initial perceived utility-value, as misalignment risks redundancy and can undermine its effectiveness. Building on this conditional perspective, future research should examine adaptive motivational scaffolds that respond dynamically to learners' individual value perceptions when engaging with GenAI-TPEK.

Our findings point to a broader challenge in AI-in-education: the

need for concrete instructional designs that foster the systematic acquisition of GenAI-TPEK knowledge. Because GenAI systems differ drastically across applications, ranging from adaptive feedback tools to automated assessment or content generation, their responsible use cannot rely on generic principles. Instead, pre-service teachers require structured opportunities to connect ethical reasoning with the specific affordances and risks of each AI implementation in educational settings.

Thus, this study contributes to the discourse on critical AI literacy by illustrating how motivational scaffolds can interact with learners' cognitive engagement in the process GenAI-TPEK knowledge integration. It emphasizes the value of integrative approaches that connect motivational and cognitive perspectives, and integrates ethics as a central knowledge domain to foster reflective and responsible engagement with GenAI in educational contexts.

Declaration of generative AI in scientific writing

During the preparation of this work, the authors used ChatGPT (version 4o) and Grammarly (version 1.122.2.0) in order to improve readability and language. After using those tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Open data

This study was preregistered at [aspredicted.org](https://aspredicted.org/zrs6-9y5b.pdf) (see <https://aspredicted.org/zrs6-9y5b.pdf>). Supplementary materials, including data sets and analysis scripts, are available on DOI https://osf.io/nx8uq/?view_only=7e3406289efb46019085cfc5c5663e4c.

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CRediT authorship contribution statement

Jana Boos: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thérèse Eder:** Writing – review & editing, Formal analysis, Conceptualization. **Andreas Lachner:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table 2
Participant Demographics by Condition.

Variable	Control condition (n = 56)	UV condition (n = 55)	UVS condition (n = 47)	Total (N = 158)
Age, <i>M</i> (<i>SD</i>)	24.18 (1.97)	24.89 (2.32)	24.34 (1.96)	24.47 (2.11)
Female, <i>n</i> (%)	38 (67.86)	38 (69.09)	31 (65.96)	107 (67.72)
Semester, <i>M</i> (<i>SD</i>)	9.70 (2.52)	9.67 (3.74)	8.94 (3.82)	9.46 (3.38)

Note. UV = utility-value intervention without scaffolding; UVS = utility-value intervention with scaffolding.

Table 3
Procedure.

Measure	Scale	Condition
Demographics*	Age, gender, language, study degree, study subjects, semester	UV, UVS, control
Intrinsic value	Four-point Likert scale [29]	UV, UVS, control
Initial perceived utility-value*	Four-point Likert scale [27]	UV, UVS, control
Academic self-concept	Four-point Likert scale [29]	UV, UVS, control
Judgment of learning	0 % to 100 % [55]	UV, UVS, control
Domain-specific knowledge (TK, EK, PK)*	Multiple choice questions (max. 12 points in total)	UV, UVS, control
Utility-value intervention*	Video with expert statements, Writing task, Quality of writing task (additive score)	UV, UVS
Learning environment*	Log files	UV, UVS, control
Mental effort learning environment	Nine-point Likert scale [56]	UV, UVS, control
Subjective difficulty	Nine-point Likert scale [57]	UV, UVS, control
Perceived utility-value at posttest*	Four-point Likert scale [27]	UV, UVS, control
Judgement of Learning	0 % (not at all confident) to 100 % (very confident) [55]	UV, UVS, control
Domain-specific knowledge (TK, EK, PK)*	Multiple choice questions (max. 12 points in total)	UV, UVS, control
Integrated knowledge*	Open-ended questions (max. 16 points in total)	UV, UVS, control
Mental effort at posttest	Nine-point Likert scale [56]	UV, UVS, control
Subjective difficulty	Nine-point Likert scale [57]	UV, UVS, control

Note. Measures marked with * are reported in this paper.

Table 4
Descriptive Statistics and Baseline Equivalence of Control Variables across Conditions.

Variable	Control Group (n = 56)	UV condition (n = 55)	UVS condition (n = 47)	<i>F</i> (2, 155)	<i>p</i>	η^2
Prior knowledge	7.29 (2.29)	7.29 (2.17)	7.55 (2.09)	0.24	.786	.00
Initial perceived utility-value	3.35 (0.53)	3.41 (0.46)	3.44 (0.46)	0.50	.609	.00
Academic self-concept (technological)	2.85 (0.52)	2.79 (0.53)	2.69 (0.58)	1.09	.340	.01
Academic self-concept (ethical)	3.18 (0.53)	3.15 (0.45)	3.1 (0.44)	0.18	.839	.00
Intrinsic value (technological)	2.78 (0.71)	2.79 (0.71)	2.70 (0.74)	0.25	.780	.00
Intrinsic value (ethical)	2.97 (0.73)	3.02 (0.58)	3.06 (0.65)	0.24	.786	.00

Note. Values are presented as *M* (*SD*). *F*- and *p*-values from one-way ANOVAs testing group differences. η^2 = eta squared as effect size. UV = utility-value intervention without scaffolding; UVS = utility-value intervention with scaffolding.

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