Personalization over Privacy? Implications of the Privacy-Personalization Trade-Off for Future Use of Intelligent Tutoring Systems

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Abstract. The low adoption of Intelligent Tutoring Systems (ITS) and other AIED tools is partly due to privacy concerns when handling student data. Previous research investigated the privacy-personalization trade-off, where users decide about using a system by contrasting the envisioned benefits against the amount of personal data required. However, related AIED research is still in its initial stages. In our study, we analyzed how usability and privacy-related factors influence university students' decision to adopt an ITS. We presented participants with three versions of an ITS, differing in the amount of data collected and - as a result - the availability and depth of educational features. We found that even though students perceived a significant difference in privacy risk across the versions, this did not influence their intention to use them. Perceived usefulness of the ITS and its personalized features, on the other hand, proved to be a strong predictor of future adoption. We deepen these findings with additional qualitative results and conclude with future recommendations to AIED researchers and developers alike.

Keywords: Intelligent Tutoring System · Privacy · Usability · Privacy-Personalization Trade-Off

1 Introduction

Intelligent tutoring Systems (ITS) have been repeatedly proven to have a positive effect on learning outcomes [15,17], through personalized features such as immediate feedback, scaffolding hints, and evaluation of student skills over time [21]. Despite these known benefits, adoption by higher education institutions has been slow. One reason behind this is the need to use rich student interaction data for these systems to work, which raises data privacy concerns [29]. These concerns differ greatly between students and contexts [28]; therefore, students have varying expectations toward AI in education (AIED) systems and the related amount of data collection [29], which makes it desirable to provide them agency over data handling to express these preferences. However, for students to exercise agency over their data responsibly, they need to be taught AI literacy [33], and provided the controls to exercise that agency [10]. To that end, we present and evaluate a prototype of an ITS that provides students with varying degrees of personalized educational features depending on the amount of data collected. At the same time, the system transparently informs users about what data is collected and the features that have been disabled due to limited access to certain data types. Through this feedback the system aims to enhance transparency and increase users' AI and privacy literacy.

We based our study on two important models related to user experience and human-centered privacy: the Technology Acceptance Model (TAM) and the privacy-personalization trade-off. Previous studies based on the TAM [6] showed the importance of perceived usefulness and perceived ease of use as well as risk perception [7] of a system as positive or negative predictors for future adoption. Additionally, the privacy-personalization trade-off [2] describes how the benefits one could gain from sharing their data can conflict with the related perceived privacy risks. The behavior of users in this regard often differs greatly from their self-reported concerns [19], as most online users disclose much more data about themselves than they intend to when asked directly. In the field of AIED, studies analyzing student privacy concerns have mainly relied on self-reports from surveys and interviews instead of experimental methods, creating an important research gap.

In our study, we aim to fill this gap by exposing students to a first-hand experience with three versions of an ITS prototype differing in the amount of data collected and the availability of certain educational features. Our goal is to understand how students evaluate the usability as well as the privacy risk of these different versions, and which of these factors have an influence on their future intention to use the system. Therefore, we defined the following research question:

RQ: How do students evaluate the usefulness, ease of use, and perceived privacy risk of different ITS versions requiring more or less user-data collection, and how do these factors affect their intention to use these versions?

To answer our research question, we use Structural Equation Modeling (SEM) to model the relationships between these constructs. Besides capturing students' perceptions of the three ITS versions, we also collected data on personal traits such as technological affinity [8] and general online privacy concerns [20] to investigate potential personal factors behind their perceptions. We complemented our findings with qualitative analysis of open-ended responses to deepen our understanding of how the privacy-personalization trade-off influences the adoption of AIED tools by students.

2 Background: Privacy in AIED Tools

Ethical and societal aspects of AI such as privacy are part of most AI literacy frameworks, but they are usually portrayed as the last step after acquiring technical and algorithmic knowledge [23]. At the same time, university students typically expect to exercise agency over data shared with AIED tools [28], which requires a good understanding of how to manage their data responsibly [33]. Yet, students often lack that skill [10]. Therefore, we aim to enhance an AIED system - specifically an ITS - with design features that make data privacy implications of using its educational features clear through short explanations and enabling or disabling certain features depending on students' willingness to share their data. These feedback features can be integrated into an ITS regardless of the learning content at hand, and can therefore efficiently educate students about implications of data use.

Privacy research has shown that privacy-related decisions not only differ between users, but also depend highly on contextual factors, such as recipient, data type, or mode of transmission [24]. This is also true in educational technologies, where students have differing views about the data they are willing to share [28,1], and how they evaluate the privacy of certain features which in turn is a significant predictor of their adoption of those features [27]. Both students and faculty consider privacy as important as the analytics aspect of learning analytics [30]. Yet, even though students express a strong desire for data privacy, they do not always act accordingly [19,30]. This is partly because of the privacy-personalization trade-off [2,9,18] referring to the fact that enjoying the benefits of personalization usually means sacrificing part of one's privacy. Users decide on that trade-off based on individual preferences and contextual factors, although mostly not in a rational way [14]. Prior studies related to this trade-off in AIED have mostly relied on survey and interview data, therefore not exposing participants to an authentic experience where their attitudes regarding data sharing could be observed in a specific context. Therefore, in our study, users directly interact with different variants of a prototype that allows for capturing their interaction experience. This also allows for collecting aspects of user experience aside from privacy that are relevant for the future adoption of AIED tools.

The Technology Acceptance Model (TAM) [6] contains two main predictors of future intention to use a system: perceived usefulness and perceived ease of use. TAM is also the most widely used adoption model in AIED [35], and related studies report varying degrees of relationships between the constructs [34]. Previous usability studies have expanded the model with the construct of risk perception that includes privacy risk [22,7] and found significant relationships between perceived risk and intention to use [7]. Moreover, [20] showed that the amount of privacy-related risk that a user associates with a digital system is influenced by their general concerns about online privacy, and in turn influences their future usage. Finally, differences in affinity for using new technologies are also considered an important factor in predicting user experience and future use [8], which also applies to the educational field [4]. Therefore, in our study we utilize and expand the TAM model with the following constructs: perceived privacy risk, general online privacy concerns and technological affinity.

3 Methods

We conducted in-person lab sessions, with $N = 126$ university students, during which they were asked to use different versions of an ITS prototype. In the following section, we describe in detail the experiment and data analysis. Supplementary materials (i.e., screenshots, codebooks, participant demographics) can be found online on OSF. Our study has been approved by the Ethics Committee of ETH Zurich, and preregistered to enhance transparency and replicability. For the purpose of the study, we did not collect personally identifiable information through the ITS to protect participants' privacy.

3.1 The ITS Prototype

The prototype used for the study was based on the tool CTAT - short for Cognitve Tutor Authoring Tools, an ITS developed by Carnegie Mellon University [31]. To account for the varying privacy preferences of students, we created three versions of a prototype with adaptations in data collection and, as a result, the availability of educational features. These three versions were:

- **Tutor A:** This version only recorded absolutely essential data from students that let the system operate, such as correctness of answers. Also, students could request a hint for a task at hand, but no additional educational features were enabled.
- **Tutor B:** The second version additionally collected and saved data about the development of student's skills, such as *identifying trends* or *estimation*. Also, the hint feature was more customizable in this version, allowing the student to select the type of hint they would like to receive.
- **Tutor C:** Finally, Tutor C contained a tutoring chatbot connected to the task space and therefore having access to the student's previous interaction with the interface to provide personalized support when asked a question. We used prompt engineering to provide adequate LLM-generated advice (e.g., providing relevant guidance instead of direct solutions to the task at hand).

For students to understand how the educational features and privacy implications of each version differ, we adopted the same screen structure for all versions. Disabled features (e.g., disabled LLM chatbot in Tutor A) were covered by a short text explaining the reason for disabling it to allow users to understand the privacy implications of varying degrees of personalization. For our study, we used educational tasks related to visualization literacy to allow for applicability to students across various disciplines. The questions were developed following the structure of the Visualization Literacy Assessment Test [16]. This allowed students to engage with the task and the available educational support features in each version. Each task consisted of one graph along with three to four related questions (multiple choice or numerical input) that tested students' ability to interpret the graph, followed by an open-ended question based on Yang et al. [36] asking them to describe the graph's main insights in 50-100 words. An example task across the three versions is shown in Figure 1.

3.2 Recruitment

The sample consisted of $N = 126$ bachelor students enrolled at ETH Zurich or University of Zurich. The minimum sample size was determined based on a simulation with estimated effect sizes between .15-.35 for all paths, alpha error probability of .05 and power of .8. Among participants, 75 were men, 49 women, one non-binary participant, and one preferred not to disclose their gender. This distribution is representative of that of the student population of the participating institutions. The average age was 21.3 (SD=2.8), ranging from 18 to 35 years. Every participant was compensated CHF 25 for one hour of participation in line with the recommendation of our institution and exceeding minimum wage requirements. Participants who took longer to finish the study and agreed to stay received additional compensation based on the amount of additional time spent.

3.3 Procedure

The experiment took place in person at our institution's lab. After reading and signing the consent form and the instructions for the study, students (1) interacted with one of the tutor versions by solving a visualization literacy task, directly followed by (2) a survey asking them about their experience with that version using validated questionnaires and open-ended questions. We measured the following constructs: Perceived Usefulness (PU) [6], Perceived Ease of Use (PEoU) [6], Perceived Privacy Risk (PPR) [3], and Intention to Use (ItU) [32]. Additionally, participants answered three open-ended questions, namely (Q1) what they liked or disliked about the version at hand, (Q2) the types of data they think was collected about them, and (Q3) whether and in what context they think they would use that ITS version in the future. In a within-subject design, steps (1) and (2) were repeated for each of the three tutor versions. Finally, (3) participants completed a final survey with additional questionnaires related to online privacy concerns (IUIPC) [20], technological affinity (ATI) [8], and questions regarding demographic information. Once a participant had completed all tasks, they could collect their compensation and leave the session. As the tutor versions differed based on an increasing number of educational features and amount of data collection from Tutor A to Tutor C, we did not fully randomize the order in which students interacted with the tutor versions. Rather, students were assigned to one of two groups: interacting with the versions in "increasing" (Version A→B→C) or "decreasing" (Version C→B→A) order. In the final sample, there were 62 participants in the first group, and 64 participants in the second group.

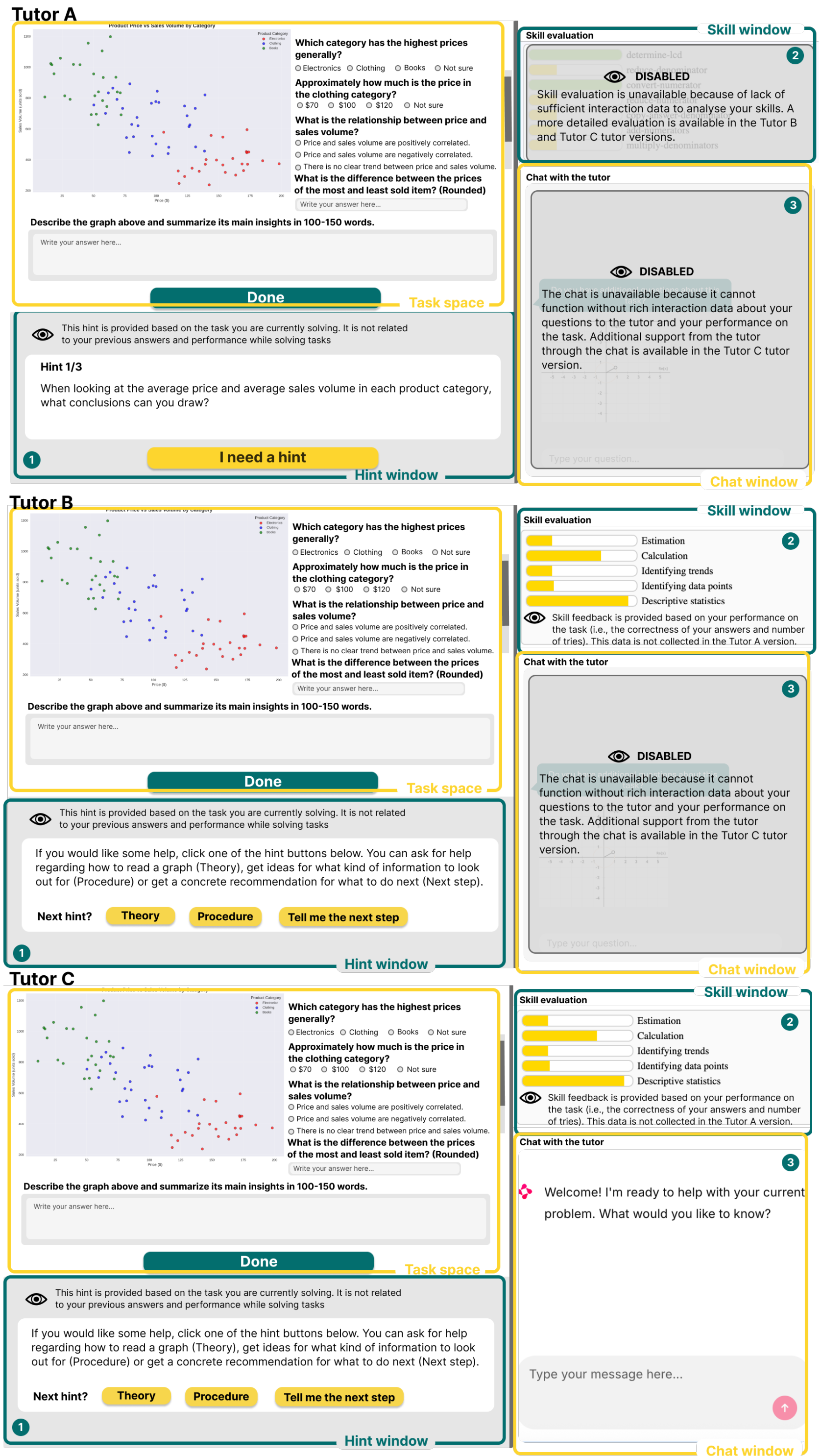


Fig. 1. An illustration of the three tutor versions. Specific features on the right side are enabled or adjusted based on the available student data. Hint window (1): In Tutor A, students passively receive general hints; in Tutors B and C, they can request specific hint types. Skill feedback (2): This feature is disabled in Tutor A. In Tutors B and C, it provides feedback based on performance across tasks. Chat window (3): Disabled in Tutors A and B. Tutor C uses generative AI to provide additional support connected to student interactions in the task space. The privacy implications of each version are explained in dedicated information boxes (marked with an eye sign).

3.4 Analysis

To answer our research question, we used Multilevel Structural Equation Modeling (MLSEM), where Level 1 (within-subjects) represents the interactions with different tutor versions and Level 2 (between-subjects) represents the individual students. Level 1 variables are therefore those measured by the three version-related surveys, and Level 2 variables were those measured in the exit survey. Figure 2 summarizes the path analysis of the MLSEM model on both the within- and between-subjects level.

Data preparation. To ensure data quality, we first screened our dataset and removed a duplicate entry based on a technical problem. There were no incomplete survey submissions in our dataset. Univariate normality was assessed using skewness and kurtosis; all items fell within acceptable ranges (skewness ± 2, kurtosis ± 7; [12]) except for one item (awa1 of the IUIPC with -2.05 skewness). This item was not removed from the dataset at this point due to being part of the validated and widely used IUIPC scale. To evaluate the necessity of a multilevel approach, we calculated the Intraclass Correlation Coefficients (ICCs) for all Level 1 items. The ICCs ranged from .22 to .50, indicating that a relevant proportion of the total variance (22%–50%) was at the between-subjects level. These values exceed the common threshold of .05 or .10 for multilevel modeling [13], confirming that MLSEM was required to account for the nested structure of the data. We additionally performed Multilevel Confirmatory Factor Analysis (MCFA) to verify the construct validity of our measures.

Model Specification. The final outcome variable in our model was *Intention to Use* as our goal was to understand how (perceived) usefulness and privacy concerns influence students' decision to use an ITS in the future. Based on our hypotheses, *Perceived Usefulness*, *Perceived Ease of Use*, and *Perceived Privacy Risks* were modeled as predictors of Intention to Use. Additionally, based on findings from previous usability research in AIED [35], we expected *Perceived Ease of Use* to also be a predictor of *Perceived Usefulness*, and thus modeled *Perceived Usefulness* as a mediator between *Perceived Ease of Use* and *Intention to Use*. In terms of the between-subjects variables, we expected the effect of *ATI* on *Intention to Use* to be mediated by *Perceived Usefulness* and *Perceived Ease of Use*. Similarly, the effect of *IUIPC* was expected to be mediated by *Perceived Privacy Risk*. We used the R lavaan package [25] to perform our analysis. Because one item exceeded the skewness threshold, we used the Robust Maximum Likelihood (MLR) estimator in our MLSEM, which is robust to non-normality.

Qualitative analysis. To deepen the understanding of students' responses to the questionnaires, we additionally analyzed students' answers to open-ended questions using an inductive thematic analysis approach [5]. We utilized an open-coding process to develop a structured codebook [11]. The qualitative answers were analyzed by two of the authors. For Q1 and Q3 (i.e., what they liked/disliked about the tool, and whether they intend to use it in the future), the authors started coding 10% of the dataset. The two created codebooks were then compared, and the researchers agreed on the final code structure. Finally, the researchers independently coded the full dataset using the final codebook, after which interrater reliability was calculated. Remaining disagreements were solved through discussion. Answers to both of these questions got assigned two codes: Code 1 classifying the valence of the response across four classes: positive, negative, mixed, or neutral/unclear, and Code 2 categorizing the specific reason provided. We achieved substantial agreement for both Q1 Code 1 (Cohen's $\kappa =$ .83) and Q3 Code 1 (Cohen's $\kappa = .87$). As the Code 2 options were not exclusive to each other, Cohen's κ was not applicable. Instead we calculated the agreement level that was .73 for Q1 and .78 for Q3. As for Q2 (the types of data students think have been collected), a deductive coding process was used, where one researcher coded the replies by sorting the mentioned types of data into the six following categories (based on the data collection capabilities of CTAT): educational, contextual, interaction, personally identifiable, personal characteristics, or other.

4 Results

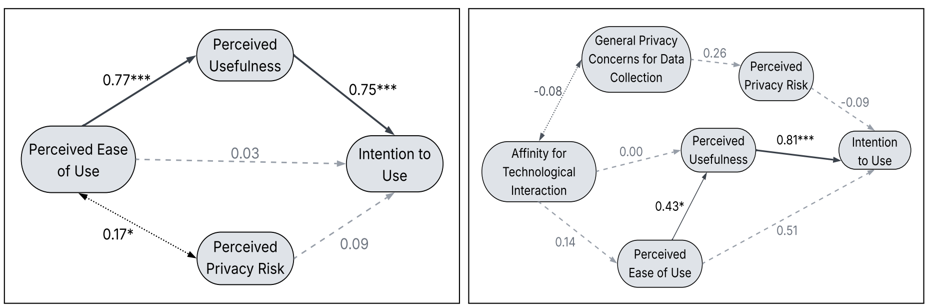
4.1 Multilevel Structural Equation Model Results

Factor Analysis. Construct validity was assessed via a two-level MCFA. On Level 1 (within-subjects level), all items exhibited significant loadings on their respective constructs ($p < .001$). On Level 2 (between-subjects level), the measurement model for individual traits (ATI and IUIPC) was similarly supported. Whereas most Level 1 items remained robust at the between-person level, one item (*peou_4*) did not significantly load onto the Level 2 *Perceived Ease of Use* factor ($p = .396$), suggesting it primarily captured situational rather than trait-based perceptions. The factor loadings of *IUIPC* show that only the "Collection" subscale (items 7–10) achieved acceptable factor loadings (>.7). To improve model fit and construct validity, we thus decided to only include the four *Collection* items in the final model, as that is also the most relevant to our research question (i.e., the different ITS versions differ in the amount of user-data collected).

Model Fit. The MLSEM yielded a good fit to the data (Robust CFI = .944; Robust TLI = .939; Robust RMSEA = .035). The SRMR was .093 at the within-subjects level and .171 at the between-subjects level. While the between-subjects SRMR is higher, the overall robust indices suggest the model is a valid representation of the data.

Within-Subjects Paths (Level 1). At the within-subjects level, which captures different perceptions across tutor versions, *Perceived Usefulness* was a strong and significant predictor of Intention to Use ($\beta = .75, p < .001$). Whereas the direct path from *Perceived Ease of Use* to *Intention to Use* was not significant ($\beta = .03, p = .738$), *Perceived Ease of Use* demonstrated a significant influence on *Intention to Use* indirectly by significantly predicting *Perceived Usefulness* ($\beta = .77, p < .001$). The path from *Perceived Privacy Risk* to *Intention to Use* was not significant ($p > .05$), suggesting that differing perceptions of privacy risk do not influence future intention to use different ITS versions. Additionally, a significant positive covariance was observed between *Perceived Ease of Use* and *Perceived Privacy Risk* ($r = .158, p = .062$), suggesting that as ease of use increased, so did students' perceptions of privacy risk.

Between-Subjects Paths (Level 2). At the between-subjects level, which captures differences between individual students, the pattern for *Intention to Use* remained consistent: *Perceived Usefulness* strongly predicted *Intention to Use* ($\beta = .81, p < .001$), accounting for 72.6% of the variance in *Intention to Use* ($R^2 = .726$). Similar to the within-level results, trait-level *Perceived Ease of Use* significantly predicted trait-level *Perceived Usefulness* ($\beta = .43, p = .020$). Also in line with the within-subjects model, *Perceived Privacy Risk* did not prove to be a significant predictor of *Intention to Use* on the trait level either. Interestingly, the direct paths of technological affinity (ATI) and global privacy concerns regarding data collection (IUIPC Collection) did not reach statistical significance ($p > .05$), suggesting that the immediate perceptions of the tutor (*Perceived Usefulness* and *Perceived Ease Of Use*) are more important drivers of adoption than general personality traits.



$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Fig. 2. Results of the MLSEM model on the within- and between-subjects level.

Further Exploratory Analysis. In addition, we performed exploratory analysis to investigate (1) how *Perceived Privacy Risk* differed across tutor versions, and (2) whether the second-order groups demonstrated any significant differences when rating Level 1 items (as the version order was not fully randomized, we wished to ensure there were no unintended order effects that could bias results). ANOVAs with *Version* and *Order* as predictors showed that for *Perceived Usefulness*, *Perceived Ease of Use*, and *Intention to Use*, only the effect of *Version* proved to be significant, while in the case of *Perceived Privacy Risks*, both the effects of Version and Order were significant. The trends of how each tutor version was rated in these dimensions is visualized on Figure 3. The plot for privacy risk shows that the significant effect of *Order* was due to the group starting with Tutor A demonstrating generally higher privacy concerns towards all versions. However, this analysis also shows that participants of both groups clearly perceived an increasing privacy risk from Tutor A to C, regardless of the order in which the versions were presented. This validates that the design of our prototype achieved the intended purpose, and that the reason for *Perceived Privacy Risk* not being a significant predictor of *Intention to Use* is not based on students' lack of understanding of privacy implications.

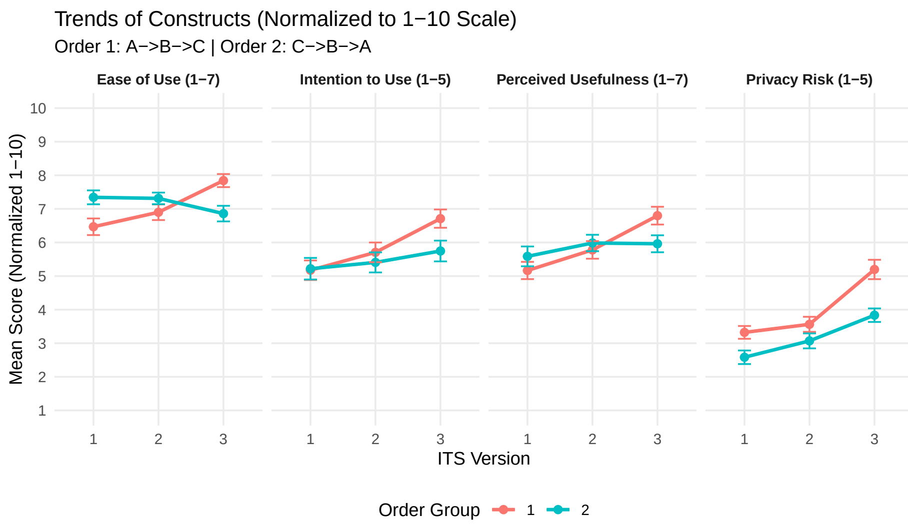


Fig. 3. The figure depicts how *Perceived Ease of Use*, *Intention to Use*, *Perceived Usefulness*, and *Perceived Privacy Risks* differ between the two groups and vary across the ITS versions. For better readability, all scales have been normalized on a 1 to 10 scale. Original scale levels are specified in parentheses along with the labels.

4.2 Qualitative Results

The qualitative responses further support our results. Key results are summarized in Tables 1,2,3 and 4. The valence of the responses provided for Q1, i.e., what students liked/disliked, was slightly more often positive (n=109) than negative (n=95), and often mixed (n=127) due to the dual nature of the question. Another n=47 were neutral or unclear responses. Numbers exceed the number of participants as participants provided responses for each of the three prototype versions. Looking at the versions separately, Tutor A received 31 positive responses, Tutor B received 38, and Tutor C received 40, which is in line with Tutor C receiving the most favorable scores in terms of usefulness in the questionnaires as well. This is probably due to the availability of the chatbot, e.g., *"The three tips (procedure, next step, etc.) weren't very helpful, while the llm agent did provide some useful insight."* (about Tutor C). The most commonly mentioned aspects that students liked/disliked were the *educational features* (n=217) and the *User Interface (UI)* (n=128), with educational features being mentioned more often in a positive light (66 positive and 87 mixed responses), while the UI was more often associated with negative responses (40 negative and 70 mixed responses). Other popular categories were the *educational content* (n=78), *usefulness/functionality* (n=72) and *understandability* (n=48). The latter have been mostly mentioned as a reason to like the tool (19 positive and 20 mixed replies), while the other two have been mentioned in close to equal amounts as positive or negative by different students.

Table 1. Results of coding for positive/negative assessment of Q1 answers for each ITS version and the total.

Code	Tutor A	Tutor B	Tutor C	Total
positive	31 (25%)	38 (30%)	40 (32%)	109 (29%)
negative	43 (34%)	31 (25%)	21 (16%)	95 (25%)
mixed	34 (27%)	44 (35%)	49 (39%)	127 (34%)
neutral or unclear	18 (14%)	13 (10%)	16 (13%)	47 (12%)

Regarding Q2 (data types students think have been collected), the majority of responses mentioned educational data, such as results and skills (n=259), followed by interaction data, such as clicks or mouse movements (n=190), e.g., *"It did not collect personal information, it only collected my understanding and reading of the provided graph."* (about Tutor C). All other data types were mentioned less frequently: personally identifiable data 33 times, contextual data (such as date, time, location) 30 times, and personal characteristics (such as style of writing) 29 times. These results show that although participants correctly identified multiple data types potentially collected by ITS, they mainly considered the most direct options and perhaps overlooked others. Whereas we did not collect personally identifiable information through the ITS in our study for privacy reasons, the system allows for the collection of all the listed data types in the case of classroom use.

Table 2. Occurrences of cited collected data types in Q2 answers for each ITS version.

Code	Tutor A	Tutor B	Tutor C	Total
educational	79	95	85	259
interaction	55	61	74	190
personally identifiable data	11	8	14	33
contextual	9	9	12	30
personal characteristics	8	10	11	29
other	23	16	13	52

Finally, responses to Q3 show that students would be interested in using at least one of the tutor versions for their studies. Once again, in line with the MLSEM results, Tutor C received the most positive and least negative responses

(91 positive and 34 negative), followed by Tutor B (76 positive and 40 negative), and finally Tutor A (74 positive and 54 negative), e.g., *"Yes, with social sciences courses; less so without the chat, though."*, (about Tutor A). . The most frequently mentioned use case for the tutor was *independent studying* (N=73), with many (N=62) mentioning that they would only use it for *specific subjects* (mainly mathematics or statistics) or *exam preparation* (N=35). A lot of participants who answered negatively did not provide additional explanation, but one relatively common reply indicated students expected low *effectiveness* (N=45) from the tool.

Table 3. Positive answers to Q3 relative to each ITS version and in total classified according to coded related themes.

Theme	**Tutor A**	**Tutor B**	**Tutor C**	**Total**
independent studying	21	22	30	73
specific subjects	17	21	24	62
assignments/homework	9	7	7	23
exam preparation	11	13	11	35
review of lectures	7	6	7	20
unclear	9	7	12	28
Total	74	76	91	241

Table 4. Negative answers to Q3 relative to each ITS version and in total classified according to coded related themes.

Theme	**Tutor A**	**Tutor B**	**Tutor C**	**Total**
AI for learning	0	0	5	5
effectiveness	18	16	11	45
UI	8	3	4	15
unclear	27	21	14	62
data collection	1	0	0	1
Total	54	40	34	128

5 Discussion and Conclusion

Our study investigated how university students' intention to use ITS differs regarding the privacy-personalization trade-off when presented with ITS versions differing in the available educational features and amount of data collected. We found that even though students are clearly aware of the differences between versions in terms of privacy risk, this does not predict their intention to use a specific version in the future which aligns with a recent related study [26]. The main aspect influencing students' intended adoption is how useful they perceive a specific version of the tool. We additionally found that the perceived ease of use is a predictor of perceived usefulness, suggesting that a smooth user experience could lead to a more positive evaluation of a system's effectiveness, which is in line with other findings from usability research [6,35]. Based on our findings, we conclude the following:

Perceived usefulness is the key to motivate students to use AIED. The strongest relationship found in our model is further supported by the qualitative results emphasizing the importance of the tool's effectiveness and the quality of the provided educational features. In contrast, data privacy was rarely mentioned as a deciding factor for future use. It is therefore important to make students aware of the specific educational benefits - while still designing with privacy and other ethical aspects in mind - when the goal is to motivate future adoption.

Transparent privacy-related feedback and first-hand experience with an ITS support students' **awareness of the data collection implications** of using its personalized educational features. We saw that participants clearly associated a higher privacy risk with tutor versions that collected more data from them. When asking them to list the types of data they think the system has access to, most of them thought of those directly identifiable from the screen, such as educational and interaction data. Whereas this is definitely a good first step toward successful user notice, the privacy-related feedback should ideally be complemented with additional AI and digital literacy training.

Finally, it is important to note that the **responsibility remains with AIED designers to ensure student privacy**, even if student agency regarding data collection is supported by a system. We saw that user experience and learning benefits are enough for students to sacrifice their data privacy, even when they associate privacy risks with an ITS. AIED designers should ensure that the privacy-personalization trade-off is as small as possible, even if a student decides not to restrict access to their data.

Our study has limitations that could be addressed by future work. First, even though we introduced three ITS versions to students, we did not actually give them a chance to freely choose between them in this study. Future work could explore whether it yields the same results when participants get to only interact with their preferred ITS version in a similar context. Additionally, other aspects of ITS, such as adaptive learning paths, have not been integrated into our prototype as of yet. As this feature would provide an even more tailored learning experience while using more student data, it would be worth exploring its possibilities in a similar multi-version structure.

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