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Modeling the Psychological Determinants of Student Adoption of Video-Enabled Feedback Tools

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Video-enabled feedback is increasingly integrated into technology-enhanced learning environments, offering rich opportunities for interaction aligned with evolving digital communication practices. However, its adoption is highly sensitive to psychological determinants such as trust, perceived risk, and perceived usefulness. This study explores how these constructs influence learners' acceptance of video-enabled feedback, conceptualized here as a strategic service design intervention. A quasi-experimental pre-test–post-test design was employed over a 10-week intervention. Data were collected from 88 high school students assigned to an experimental group (video feedback) and a control group (text feedback). The data were analyzed using partial least squares structural equation modeling (PLS-SEM). The findings revealed that exposure to video feedback significantly increased trust and perceived usefulness while decreasing perceived risk. Furthermore, perceived usefulness and trust strongly predicted student satisfaction, which in turn served as a central mediator driving both continuance intention and the willingness to invest in personalized learning (WIPL). Perceived risk, conversely, negatively affected trust and satisfaction. The study also highlights the moderating roles of individual differences: virtual risk sensitivity amplified the effects of risk perceptions, whereas creative thinking and self-regulation strengthened the impact of perceived usefulness on satisfaction. These results demonstrate that the acceptance of digital educational tools depends critically on mitigating psychological barriers. By integrating the Technology Acceptance Model (TAM) and Expectation Confirmation Model (ECM) with a trust-risk framework, this research offers practical implications for EdTech developers to design trustworthy, user-centered systems that foster sustainable user engagement and revenue models.

Introduction

Internet-based educational technologies (EdTech) continue to proliferate, and video-enabled feedback significantly enhances instructor-student interaction and user experience. Despite its potential, video-enabled feedback is highly sensitive to psychological determinants

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such as trust, perceived risk, and perceived usefulness (PU). Studies across various digital contexts, from children's platforms (Zhu, Zhai & Li, 2025) to mobile wallets (Tripathi, 2023) and travel applications (Liu et al., 2020), suggest that trust and perceived risk are key factors in shaping engagement. However, these relationships have not been sufficiently explored within the specific context of video-enabled feedback. In the digital learning ecosystem, service design involves the integration of feedback mechanisms that create a holistic user experience. Video-enabled feedback, characterized by personalized audio and visual responses, is gaining attention due to its positive impact on understanding and engagement in K-12 and higher education (Arslankara & Seferoğlu, 2024; Kim & Ammeter, 2018). Existing evidence suggests that video-enabled feedback may outperform written feedback by reducing uncertainty and increasing perceived diagnosticity through media richness (Daft & Lengel, 1986; Noetel et al., 2021). In this study, these fragmented findings are integrated into a combined structural model to evaluate the impact of video-enabled feedback, as a service design element, on trust, risk, PU, student satisfaction, and behavioral intentions.

Theoretically, some studies have integrated technology acceptance models, such as TAM, UTAUT, and ECM-ISC, with trust–risk frameworks in the EdTech domain. Although PU and satisfaction are identified drivers of e-learning continuity (Bhattacherjee, 2001; Venkatesh et al., 2003), increasing data tracking in Learning Management Systems (LMS) raises learners' privacy concerns. This tension between trust and perceived risk has become a critical mechanism for platform sustainability (Liu & Khalil, 2023; Kwapisz et al., 2024). Furthermore, much EdTech research focuses heavily on initial adoption and often overlooks high-commitment outcomes, such as the willingness to invest in personalized learning (WIPL). By incorporating the price-value concept from UTAUT2 (Venkatesh, Thong & Xu, 2012), this study addresses the gap in understanding the dual role of student satisfaction in predicting both continuance intention and WIPL. Individual differences also play a significant role. Virtual risk sensitivity, creative thinking, and self-regulation can systematically alter trust and PU assessments (Viberg et al., 2023; Kizilcec et al., 2017). In this study, these variables are included as moderators to provide a more detailed account of video-enabled feedback adoption. By addressing these gaps with a quasi-experimental design and PLS-SEM, this research clarifies how specific features reshape perceptions of trust and risk on the trust-privacy axis of EdTech.

Finally, while the term intention to pay (PI) is used to ensure consistency with the TAM and service design literature, in this study it is conceptualized as Willingness to Invest in Personalized Learning (WIPL). This construct reframes financial commitment as an indicator of the learner's perceived educational value and willingness to allocate resources for highly fidelity, personalized interactions. Throughout this article, PI is positioned as an indicator of the value of personalized learning services by the learner.

The research questions are structured as follows:

RQ1. Does the video-enabled feedback feature significantly influence students' levels of trust, perceived risk, and perceived usefulness (PU)?

RQ2. How do trust, perceived risk, and PU explain student satisfaction, as well as continuance intention and the willingness to invest in personalized learning (WIPL)?

RQ3. Do virtual risk sensitivity, creative thinking, and self-regulation moderate the relationships among these variables?

These research questions directly bridge the gaps identified above. Through RQ1, the direct effects of the video-enabled feedback feature on trust, perceived risk, and PU were tested. RQ2 examined how trust, perceived risk, and PU explain satisfaction, continuance intention, and WIPL. RQ3, in turn, examined whether virtual risk sensitivity, creative thinking, and self-regulation moderate these relationships. RQ1–RQ3 are respectively associated with hypotheses H1–H3, H4–H11, and H12–H14. In this way, this study presents an integrated model that connects TAM/UTAUT, ECM-ISC, and trust–risk integration within the EdTech context through the lenses of media richness, perceived diagnosticity, and service design (Davis, 1989; Venkatesh et al., 2003; Bhattacherjee, 2001; Pavlou, 2003; Jiang & Benbasat, 2007).

This research proposes an integrated framework that moves beyond conventional technology adoption by positioning video-enabled feedback as a strategic service design intervention. In the complex digital learning ecosystem, the mere presence of functional benefits (perceived usefulness) is insufficient to guarantee long-term engagement if psychological barriers, specifically the tension between trust and perceived risk, are not addressed. By synthesizing the functionalist perspective of TAM/UTAUT with the emotional and evaluative dimensions of the ECM-ISC and trust–risk theories, this study clarifies how high-fidelity pedagogical interactions can mitigate learner uncertainty. Ultimately, the proposed model aims to demonstrate that fostering student satisfaction through enhanced trust and reduced risk is the primary mechanism for transforming a routine educational interaction into a sustainable, learner-centered service experience, reflected in both continuance intention and the willingness to invest in personalized learning (WIPL).

Hypothesis

The integration of perceived usefulness (PU) and behavioral intention from the TAM/UTAUT model, the satisfaction–continuance relationship from the ECM-ISC model, and trust and risk theories (Kim, Ferrin & Rao, 2008) is formulated in conjunction with the concept of video-based service design in EdTech as follows:

H1. Exposure to video-enabled feedback features positively influences student trust toward the system.

H2. Exposure to video-enabled feedback features negatively influences students’ perceived risk regarding the system.

H3. Exposure to video-enabled feedback features positively influences students’ evaluations of perceived usefulness (PU).

H4. Students’ perceived risk negatively influences their trust in the system.

H5. The level of perceived risk negatively influences students’ satisfaction with the video feedback system.

H6. Trust in the system positively increases student satisfaction.

H7. Perceived usefulness (PU) of the system has a positive effect on student satisfaction.

H8. Student satisfaction positively predicts continuance intention regarding the future use of the system.

H9. Student satisfaction positively influences students' willingness to invest in personalized learning (PI/WIPL).

H10. Trust in the system directly and positively influences students' continuance intention, independent of satisfaction.

H11. Satisfaction plays a significant mediating role in the effects of trust and perceived usefulness on continuance intention and PI/WIPL.

H12. Among students with high virtual risk sensitivity, the effect of system features on increasing trust and reducing perceived risk is stronger compared to students with low sensitivity.

H13. Among students with high levels of creative thinking, the effect of perceived usefulness on satisfaction (and thereby indirectly on WIPL) is stronger.

Theoretical Background

In this study, video-enabled feedback is conceptualized as a service design intervention that reduces user uncertainty and increases trust. By employing rich media (audiovisual and dynamic content), this feature enhances perceived diagnosticity and perceived usefulness (PU) while reducing perceived risk, and is interpreted through media richness theory (Cheng, Shao & Zhang, 2022; Jiang & Benbasat, 2007). Post-adoption behaviors are based on three integrated frameworks: the Technology Acceptance Model (TAM), which emphasizes perceived usefulness (PU), the Unified Theory of Acceptance and Use of Technology (UTAUT), which incorporates social influence and performance expectancy (Venkatesh et al., 2003), and the Expectation Confirmation Model (ECM-ISC), which identifies satisfaction as the primary driver of continuance (Bhattacherjee, 2001). The integration of these models demonstrates that video-enabled features enhance personalized learning (PU) and satisfaction, ultimately fostering both continuance intention and the willingness to invest in personalized learning (WIPL). In digital environments characterized by high uncertainty (e.g., data privacy, performance), trust and perceived risk have critical direct and indirect effects on behavioral intentions (Pavlou, 2003; Gefen, Karahanna & Straub, 2003). While multidimensional risk perceptions, particularly performance and privacy risks, hinder adoption (Featherman & Pavlou, 2003), trust acts as a countermeasure that mitigates perceived risk and strengthens transaction intentions (McKnight et al., 2002). According to recent meta-analyses, trust and risk form a fundamental chain leading to satisfaction and loyalty (Kim & Peterson, 2022; Handoyo, 2024). In this study, these dynamics are applied to the service feature level, suggesting that video feedback increases transparency and identifiability, thus strengthening the trust–risk–usefulness pathway (Zhang, 2023).

Furthermore, student satisfaction acts as a central bridge in the post-adoption phase. Prior research suggests that the trust–risk–satisfaction chain extends beyond mere usage to monetization and subscription behaviors (Li, Liu & Chen, 2025; Soren & Chakraborty, 2024). Therefore, platform sustainability is explained through these common behavioral determinants. Finally, the strength of these relationships is moderated by individual differences. High risk sensitivity is expected to enhance the feature's effects on trust and risk mitigation (Kim & Peterson, 2022). On the other hand, personal innovativeness and creative thinking, along with self-regulation, are expected to strengthen the path from PU to satisfaction and continuance intention, as well as the willingness to invest in personalized learning (WIPL), as highly innovative users internalize the benefits of technology-mediated learning more easily (Agarwal & Prasad, 1998; Wu & Yu, 2022).

Literature Review

Instructional research indicates that video-enabled feedback may significantly outperform written comments in terms of student feedback viewing rates and academic performance (Noetel et al., 2021; Máñez et al., 2025). Within the media richness framework, these effects are attributed to increased perceived diagnosticity and social presence, which reduce learner uncertainty (Jiang & Benbasat, 2007). In the information systems domain, the ECM-ISC model has established student satisfaction and perceived usefulness (PU) as the primary drivers of e-learning continuance (Bhattacherjee, 2001; Roca et al., 2006). Large-scale studies in MOOCs further support these indirect effects (Alraimi et al., 2015).

However, the rapid adoption of learning analytics has heightened student concerns regarding data privacy, positioning trust and perceived risk as critical determinants of platform engagement (Liu & Khalil, 2023; Kwapisz et al., 2024). While e-commerce literature suggests that perceived risk weakens trust (McKnight et al., 2002; Pavlou, 2003), few studies have explored how specific features like video-enabled feedback rebalance this trust–risk dynamic in EdTech.

Furthermore, sustainable EdTech implementations increasingly rely on continuous-use frameworks. Integrating UTAUT2's "price value" construct suggests that student satisfaction and perceived usefulness (PU) are decisive for the willingness to invest in personalized learning (WIPL) (Venkatesh et al., 2012; Wang et al., 2025). Individual differences also moderate these pathways; virtual risk sensitivity may hinder trust formation, while creative thinking and self-regulation can amplify PU and satisfaction evaluations (Kizilcec et al., 2017; Viberg et al., 2023).

Despite fragmented research on technology-mediated trust or general pedagogical outcomes (e.g., Pitts & Motamedi, 2025), a significant gap remains: the empirical testing of a unified model linking video-based service design to the trust–risk–PU–satisfaction–WIPL chain. This study addresses this gap by integrating these constructs into an expanded model analyzed via PLS-SEM, offering a comprehensive understanding of both theoretical adoption mechanisms and practical platform sustainability.

Materials and Methods

This section details the implementation, participants, instruments, and analytical procedures of the study.

Research Design and Participants

This study employed a quasi-experimental pre-test–post-test design with a control group (Campbell & Stanley, 1963). Since random assignment was not feasible in a formal school setting, group assignment was conducted at the grade level. Equivalence between groups was assessed through pre-test measures and demographic variables. The sample consisted of 88 high school students (N=88) who actively used a digital learning platform. This sample size met the requirements of the "10-times rule" for PLS-SEM and provided statistical power above 80% to detect moderate effect sizes ($f^2 \approx .15$) (Hair et al., 2017; Faul et al., 2009). Inclusion criteria required active platform use, consistent participation throughout the intervention, and formal consent. To control for confounding effects, demographic variables and platform experience were compared during the pre-test phase. Moderator variables included virtual risk sensitivity, creative thinking, and self-regulation. Common method variance (CMV) was addressed using anonymization of participants, random item ordering, and various scale reference points (Podsakoff et al., 2003).

The implementation of the quasi-experimental process, including group assignments and the timeline of the intervention, is systematically detailed in Table 1.

Table 1. Overview of the Experimental Procedure and Intervention Phases

Phase	Process / Implementation
Sample Assignment	As random assignment at the individual level was not feasible in a formal school setting, groups were assigned at the grade level to maintain ecological validity.
Duration	A total of a 10-week intervention period was implemented.
Intervention (Experimental)	Students received weekly personalized feedback via screen recordings with integrated audio narration.
Intervention (Control)	Students followed the same curriculum but received only standard text-based feedback.
Control Mechanism	Baseline equivalence between groups was verified through pre-test (Week 0) measures and an analysis of demographic variables.

Measurement Model

In this study, video-enabled feedback is conceptualized as a service design intervention. Exposure to this feature (Coded: Experimental = 1, Control = 0) is modeled to test its impact on trust, perceived risk, and perceived usefulness (PU), and its subsequent effects on student satisfaction, continuance intention, and the willingness to invest in personalized learning (WIPL). The research framework integrates the role of PU from TAM/UTAUT, the function of student satisfaction from ECM-ISC, and trust–risk dynamics originally established in online transaction environments.

Rich media presentation, characterized by vibrancy and interaction, increases perceived diagnosticity in online learning assessments. This increased diagnosticity strengthens decision confidence, reduces perceived risk, and supports both PU and trust. By positioning video-enabled feedback as a functional service feature, this study parallels findings in the literature (Jiang & Benbasat, 2007) demonstrating that interactive presentations positively influence behavioral intentions through improved assessment accuracy.

In digital environments, platform trust and multidimensional risk perceptions (performance, privacy, and financial risks) are key determinants of behavior. Perceived risk often weakens trust and satisfaction, while trust increases behavioral intentions both directly and indirectly. This trust–risk axis, well-known in the foundational information systems literature (Pavlou, 2003; McKnight et al., 2002), is here translated into the EdTech context to explain how high-accuracy feedback reshapes student adoption.

Finally, in the ECM-ISC model, student satisfaction is identified as the primary driver of continuance intention. In contemporary digital services, satisfaction acts as a central mediator linking cognitive assessments to behavioral outcomes. Consequently, this model predicts that student satisfaction will not only drive continuance intention but also facilitate the willingness to invest in personalized learning (WIPL) by reflecting the value the student places on a personalized service experience.

Structural Relationships and Hypothesized Paths

In the proposed research model, feature exposure is treated as an external design input, and the following directional paths are hypothesized (see Figure 1).

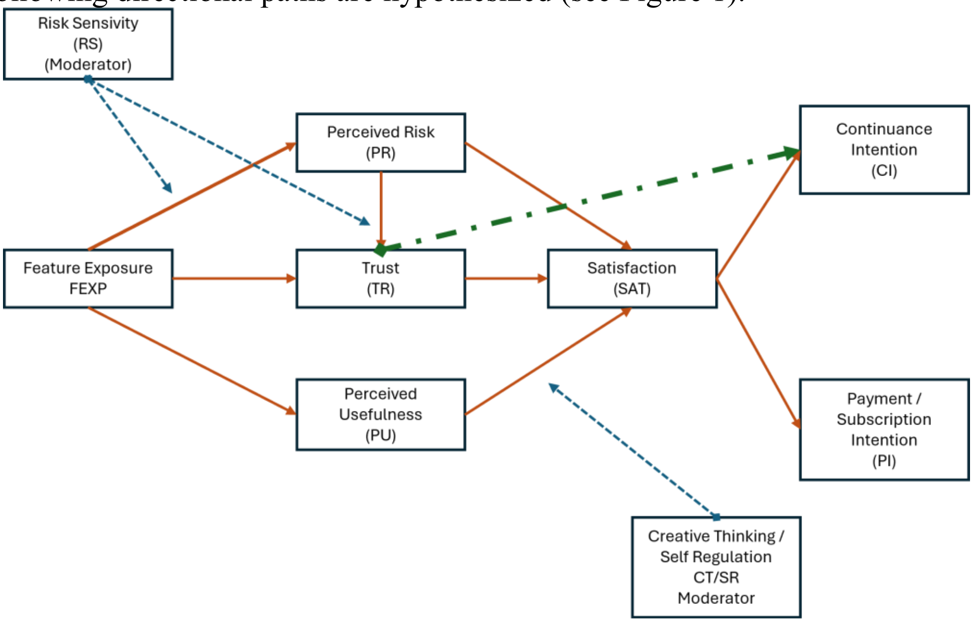

Figure 1. Research Model

This model demonstrates that users' exposure to video-based features on an EdTech platform positively influences trust, reduces perceived risk, and enhances perceived usefulness (PU). All three factors positively impact student satisfaction, which in turn has a significant positive effect on both continuance intention and the willingness to invest in personalized learning (WIPL). On the other hand, perceived risk is found to negatively affect both trust and satisfaction.

The model also accounts for two key moderation effects: students' virtual risk sensitivity shapes the relationships between feature exposure and both perceived risk and trust, while creative thinking and self-regulation influence the impact of perceived usefulness on student satisfaction.

Table 2. Latent Constructs and Definitions

Code	Construct	Definition (within study context)
FEXP	Feature Exposure (observed)	Exposure to the video-enabled feedback feature (0 = Control, 1 = Feature)
TR	Trust	Student's belief that the platform is honest, reliable, and delivers on its promises
PR	Perceived Risk	Perception that using the platform may involve privacy, performance, or financial risks
PU	Perceived Usefulness	Evaluation that the feature improves the student's learning efficiency and academic goals
SAT	Satisfaction	Overall student satisfaction with the feedback experience
CI	Continuance Intention	Student's intention to continue using the platform in the future
WIPL	Willingness to Invest in Personalized Learning	Student's willingness to allocate financial or personal resources to obtain highly tailored learning experiences
RS	Online Risk Sensitivity (moderator)	General tendency or sensitivity toward potential risks in online learning environments
CT	Creative Thinking / Self-Regulation (mod.)	Tendencies toward trying new approaches, monitoring performance, and self-regulating tasks

Table 2 summarizes the latent constructs employed in this study, providing the contextual definition of each construct and its theoretical grounding. Except for the observed variable "Feature Exposure," all remaining constructs (e.g., trust, perceived risk, perceived usefulness, and student satisfaction) are modeled as latent variables intended to explain student attitudes and behaviors. In addition, the two moderator variables (virtual risk sensitivity and creative thinking/self-regulation) represent individual differences that influence the relationships among the constructs. The measurement indicators are presented in Table 3.

Table 3. Measurement Indicators

Code	Item
TR1	"I can trust this platform."
TR2	"The platform keeps its promises."
TR3	"The platform offers reliable service."
PR1	"Using the platform is risky in terms of privacy."
PR2	"There is a risk it won't perform as expected."
PR3	"Payment/subscription is financially risky."
PR4	"Overall, this platform is risky."
PU1	"The video feedback feature makes the platform more useful."
PU2	"This feature helps me achieve my goals."
PU3	"This feature increases my efficiency."
SAT1	"Overall, I am satisfied with this platform."
SAT2	"My experience with the platform met my expectations."
SAT3	"My experience with the platform was positive."
CI1	"I intend to continue using the platform in the future."
CI2	"I plan to use the platform frequently."
CI3	"I am willing to continue using it."
PI1	"I would consider investing in/resourceally allocating funds to tools that personalize my learning process (e.g., video feedback)."
PI2	"I am willing to invest in (subscribe to) a suitable plan that offers a personalized learning experience and guidance tailored specifically to me."
PI3	"I am eager to invest in such services that add value to my learning journey and have strong diagnostic power."
RS1	"I'm sensitive to online risks."
RS2	"I'm hesitant to share personal info online."
RS3	"I avoid platforms I don't trust."
CT1	"I like trying new approaches."
CT2	"I plan and monitor my tasks."
CT3	"I come up with alternative solutions when I struggle."
CT4	"I reflect on and revise my own performance."

Experimental Procedure and Timeline

In the experimental intervention, video-enabled feedback (experimental group) was compared with text-based feedback (control group) over a 10-week period, while keeping the curriculum, duration, and assessment methods constant. Teachers implemented the intervention according to standardized training and assessment criteria to ensure treatment fidelity (Bellg et al., 2004). In Week 0 (Pre-test), demographic data, virtual risk sensitivity, and baseline data on creative thinking and self-regulation were collected to verify the equivalence of the groups. In Weeks 1–10 (Intervention), weekly learning tasks were assigned. The experimental group received video-enabled feedback (screen recording and audio), while the control group received standard text-based feedback. In Week 10 (Post-test), the core constructs (trust, perceived risk, perceived usefulness, student satisfaction, continuance intention, and WIPL) and a manipulation check were measured (Perdue & Summers, 1986).

Measurement Instruments and Data Collection

The psychometric evaluation was conducted using 5-point Likert-type scales ranging from 'Strongly Disagree' (1) to 'Strongly Agree' (5). To ensure a robust conceptual framework and content validity, all constructs were adapted from established literature and tailored to the EdTech service design context. Trust (TR) was operationalized through a 3-item scale adapted from McKnight et al. (2002) and Pavlou (2003), focusing on platform reliability. Perceived Risk (PR) utilized a 4-item instrument integrating multidimensional risk perceptions to capture privacy and performance concerns (Arslankara & Usta, 2018; Featherman & Pavlou, 2003).

For the core acceptance variables, 3-item scales for Perceived Usefulness (PU) and student satisfaction (SAT) were drawn from Davis (1989) and Bhattacherjee (2001), evaluating the added value and overall experience of the video feedback feature. Behavioral outcomes were measured via a 3-item Continuance Intention (CI) scale (Bhattacherjee, 2001) and a 3-item willingness to invest in personalized learning (WIPL) scale, specifically adapted to assess learners' willingness to invest in personalized learning services.

Individual differences were incorporated as moderating variables. Online Risk Sensitivity (RS) was assessed with a 3-item scale based on Malhotra et al. (2004), while the moderator variable of creative thinking and self-regulation (CT) was measured through a 4-item synthesis of the MSLQ (Pintrich et al., 1991) and creative self-efficacy frameworks (Tierney & Farmer, 2002). To minimize common method variance (CMV), the study employed procedural safeguards such as randomized item ordering and guaranteed respondent anonymity.

Translation and Cultural Adaptation

A rigorous cultural adaptation process was followed to ensure the linguistic equivalence of the measurement instruments. The scales were subjected to a forward–backward translation procedure (Brislin, 1970) with an expert panel of three academics. Discrepancies were resolved with two rounds of the Delphi technique, and content validity was quantified using the Content Validity Ratio (CVR) and Index (CVI) frameworks (Lynn, 1986). Prior to the main study, cognitive interviews and a pilot test (n = 30) were conducted to validate the clarity and interpretability of the items, which required minor word adjustments for the high school student population (Beaton et al., 2000; Willis, 2005).

Data Analysis

The conceptual model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4, following a two-stage evaluation of the measurement and structural models. While some traditional modeling techniques require very large samples, PLS-SEM is specifically recognized for its robust estimation performance with relatively smaller cohorts.

An a priori power analysis using G*Power 3.1 confirmed that the final sample of N=88 exceeds the minimum requirement of N=77 needed to detect medium effect sizes ($f^2 = 0.15$) at a power of .80. Furthermore, the sample size rigorously satisfies the '10-times rule,' as it significantly exceeds ten times the maximum number of structural paths directed at any latent construct in the model. Following the recommendations of Hair et al. (2019), the use of PLS-SEM in this study is methodologically justified as it provides adequate statistical power even in complex models with smaller sample sizes, ensuring the stability and reliability of the path coefficients.

Measurement and Structural Model Evaluation

Reflective indicators were assessed for internal consistency reliability using Cronbach's alpha and Composite Reliability ($\rho_C \geq 70$). Convergent validity was established through Average Variance Extracted (AVE ≥ .50), while discriminant validity was confirmed using the HTMT ratio (< .85) and Henseler's criteria (Henseler, Ringle & Sarstedt, 2015). Collinearity was monitored via Variance Inflation Factors (VIF), with values below 3.3 suggesting that the model is free from critical multicollinearity and potential common method variance (CMV) issues (Kock, 2015; Podsakoff et al., 2003).

The structural model was evaluated using path coefficients (ß), significance levels via 5,000 bootstrap iterations, and explained variance (R^2). Predictive relevance was assessed through blindfolding-based Q^2 assessment and the PLSpredict procedure (Shmueli et al., 2016). Mediation effects were analyzed following Preacher and Hayes (2008), while moderation effects (RS and CT) were tested using the two-stage product indicator method.

To validate the robust differences between the experimental and control groups across the entire structural model, measurement invariance was established via the MICOM procedure before conducting PLS-MGA (Hair et al., 2017). Analysis reporting adhered to the TREND statement guidelines for quasi-experimental research (Des Jarlais et al., 2004).

Results

Descriptive Statistics

The final sample comprised 88 participants (Experimental n=45; Control n=43). Preliminary analysis confirmed group equivalence regarding age, gender, platform experience, and moderator variables (RS, CT), with all p > .10. This baseline consistency helped support the internal validity of the subsequent structural model (Campbell & Stanley, 1963).

Table 4. Descriptive statistics and correlations at the construct level

Factor	Mean	SD	1	2	3	4	5	6	7	8
TR	3.85	0.74	—							
PR	2.71	0.79	−.45	—						
PU	3.92	0.68	.58	−.39	—					
SAT	3.78	0.72	.64	−.41	.70	—				
CI	3.95	0.70	.52	−.33	.57	.74	—			
WIPL	3.45	0.83	.47	−.30	.51	.68	.62	—		
RS	3.10	0.85	−.18	.26	−.15	−.10	−.08	−.06	—	
CT	3.60	0.73	.21	−.14	.23	.26	.20	.18	−.05	—

Construct-level descriptive statistics and correlations were summarized in Table 4. Significant positive correlations were observed between Trust (TR) and key outcomes, such as Satisfaction (SAT) and Continuance Intention (CI) (r = .64, p < .01). Conversely, Perceived Risk (PR) exhibited significant negative correlations with Perceived Usefulness (PU) (r = -.39, p < .05) and other intention-based variables, suggesting that higher risk perceptions inversely affect user evaluations, continuance intention, and WIPL.

Manipulation Check and Intervention Fidelity

The experimental group reported a significantly higher perceived video feedback experience quality (M = 4.21, SD = 0.59) compared to the control group (M = 2.05, SD = 0.81; $t_{(86)} = 9.32$, $p < .001$, $d = 1.99$). Intervention fidelity, assessed via independent rater evaluation of a 10% random sample, demonstrated high inter-rater reliability (ICC = .86, 95% CI [.78, .91]), confirming adherence to the feedback protocols (Bellg et al., 2004).

Measurement Model (PLS-SEM, Stage 1)

The measurement model was assessed for reliability and validity following the procedures outlined by Hair et al. (2017). As shown in Table 5, all standardized indicator loadings exceeded the .708 threshold, ranging from .78 to .90 ($p < .001$). Bootstrapping results further supported indicator robustness, with narrow 95% confidence intervals and low standard errors (SE: .03–.06).

Construct reliability and convergent validity were established, with composite reliability (CR) values ranging from .87 to .92 and Average Variance Extracted (AVE) values between .65 and .79, all surpassing the recommended benchmarks. Discriminant validity was confirmed through HTMT values below .85 and the Fornell–Larcker criterion. The model exhibited acceptable fit and minimal collinearity (SRMR = 0.059; Inner VIF ≤ 2.10).

Outer Loadings

All standardized indicator loadings ranged from .78 to .90 and were statistically significant according to bootstrapping ($p < .001$). Detailed results are presented in Table 5.

Table 5. Outer loadings, standard errors, and confidence intervals of the measurement model

Factor	Indicator	λ	SE	95% CI
TR	TR1/TR2/TR3	.86/.87/.85	.03–.04	[.77, .95]
PR	PR1–PR4	.78–.84	.05–.06	[.62, .91]
PU	PU1–PU3	.85–.88	.03–.04	[.77, .93]
SAT	SAT1–SAT3	.88–.90	.03	[.81, .95]
CI	CI1–CI3	.86–.90	.03–.04	[.78, .95]
PI	PI1–PI3	.85–.88	.03–.04	[.77, .93]
RS	RS1–RS3	.80–.85	.05–.06	[.65, .92]
CT	CT1–CT4	.79–.83	.05–.06	[.64, .90]

The outer loadings of all constructs in the study ranged from .78 to .90, indicating a high level of indicator reliability. Bootstrap analyses revealed that all loadings were statistically significant ($p<.001$). Standard errors were low for each indicator (ranging from .03 to .06), and the 95% confidence intervals were narrow, further supporting the robustness of the indicators.

Internal Consistency and Convergent Validity

All constructs demonstrated CR values ≥ .87 and AVE values ≥ .65 (see Table 6), indicating that both internal consistency and convergent validity were satisfactorily achieved (Fornell & Larcker, 1981; Hair et al., 2019).

Table 6. Internal consistency and convergent validity values of the constructs in the scale

Factor	α	ρA	CR	AVE
TR	.83	.84	.90	.75
PR	.81	.82	.88	.65
PU	.84	.85	.90	.75
SAT	.86	.87	.92	.79
CI	.85	.86	.91	.77
PI	.84	.85	.90	.75
RS	.78	.79	.87	.69
CT	.82	.83	.88	.65

As detailed in Table 5, all latent constructs demonstrated strong internal consistency and convergent validity. The Cronbach's alpha (α), Dijkstra–Henseler's (ρa), and composite reliability (CR) values for all constructs consistently exceeded the recommended .70 threshold, while the Average Variance Extracted (AVE) values systematically surpassed the .50 benchmark, confirming the reliability and validity of the measurement model.

Discriminant Validity

The Fornell–Larcker criterion was met. All HTMT values were below the threshold of .85 (Table 7), indicating that discriminant validity was established (Henseler, Ringle, & Sarstedt, 2015).

Table 7. Fornell-Larcker Criterion (diagonal = √AVE) / HTMT (upper triangle)

Factor	TR	PR	PU	SAT	CI	PI
TR	.866	.49	.62	.68	.55	.49
PR	.45	.806	.41	.44	.36	.31
PU	.58	.39	.866	.71	.60	.54
SAT	.64	.41	.70	.889	.77	.73
CI	.52	.33	.57	.74	.877	.68
PI	.47	.30	.51	.68	.62	.866

The fact that the √AVE values on the diagonal are higher than the correlations in their respective rows and columns indicates that discriminant validity is achieved. Furthermore, HTMT ratios remaining below the .85 threshold suggest that the constructs do not exhibit high similarity and are conceptually distinct. These findings support that the subdimensions of the scale are distinguishable from one another.

Collinearity and Model Fit Indicators

An examination of the inner VIF values (≤ 2.10) indicates that no evidence of problematic collinearity was observed in the structural model. The model fit criteria met recommended thresholds (SRMR = 0.059 and NFI = 0.912), with both the unweighted least squares discrepancy (d_{ULS}) and and the geodesic discrepancy (d_G) falling below the upper bounds of their respective 95% bootstrap confidence intervals ($d_{ULS} < HI_{95}$; $d_G < HI_{95}$). Collectively, these indices demonstrate that the overall model fit is acceptable (Henseler, Hubona, & Ray, 2016).

Structural Model (PLS-SEM, Stage 2) and Hypothesis Testing

The first research question was formulated as follows: "Does the video-enabled feedback feature have a significant effect on trust, perceived risk, and perceived usefulness (PU)? (H1–H3)". The findings from the path analyses are presented in Table 8.

Table 8. Paths from feature exposure (FEXP) to key determinants

Hypothesis	Path	β	t	p	f^2	Decision
H1	FEXP → TR	.32	4.11	<.001	.12	Supported
H2	FEXP → PR	−.28	3.22	.001	.08	Supported
H3	FEXP → PU	.35	4.58	<.001	.14	Supported

Exposure to the video feedback feature significantly increases trust (β = .32) and decreases perceived risk (β = −.28). Additionally, it contributes to users' perceived usefulness of the platform (β = .35). The effect sizes are in the small-to-medium range (f^2 = .08–.14), indicating practical significance.

The decrease in perceived risk and the increase in trust and perceived usefulness are important antecedents that contribute to the satisfaction and intention outcomes explored in the subsequent research question. The R^2 values are TR = .23, PR = .08, and PU = .12, with perceived risk also negatively affecting trust. Notably, the variance explained in trust and perceived usefulness is substantial within this experimental context. These findings align with the existing literature suggesting that rich and evidence-based presentations reduce uncertainty, build trust, and enhance perceived value (Jiang & Benbasat, 2007; Pavlou, 2003).

The second research question was formulated as follows: "How do trust, perceived risk, and perceived usefulness (PU) explain student satisfaction (SAT), continuance intention (CI), and the willingness to invest in personalized learning (WIPL)?". The findings obtained through the path and mediation analyses are presented in Table 9.

Table 9. Main paths (Determinants of satisfaction and intention)

Hypothesis	Path	β	t	p	f^2	Decision
H4	PR → TR	−.24	2.83	.005	.07	Supported
H5	PR → SAT	−.18	2.07	.039	.04	Supported
H6	TR → SAT	.29	3.64	<.001	.10	Supported
H7	PU → SAT	.41	5.31	<.001	.23	Supported
H8	SAT → CI	.54	7.12	<.001	.41	Supported
H9	SAT → PI	.46	5.91	<.001	.29	Supported
H10	TR → CI	.10	1.48	.139	.02	Not supported

The model produced R^2 values of .62 for satisfaction, .49 for continuance intention, and .41 for payment/subscription intention, indicating a moderate to high level of explanatory power. The Q^2 values (SAT = .41; CI = .32; PI = .26) also reflect positive predictive relevance.

Perceived risk negatively influences both trust (β = −.24) and satisfaction (β = −.18), reaffirming the fundamental role of risk-sensitive evaluations in e-commerce settings (Pavlou, 2003).

Trust (β = .29) and especially perceived usefulness (PU) (β = .41) are strong predictors of satisfaction with PU making a greater contribution (f^2 = .23). This suggests that the increase in perceived functional value due to the feature directly translates into evaluative responses such as satisfaction (Davis, 1989; Bhattacherjee, 2001).

Student satisfaction is the strongest predictor of both continuance intention (β = .54) and the willingness to invest in personalized learning (WIPL) (β = .46), aligning with the Expectation

Confirmation Model (Bhattacherjee, 2001).

The non-significance of the direct TR → CI path indicates that continuance intention is largely shaped by satisfaction. In other words, the behavioral effects of trust are transmitted through student satisfaction (see Table 10).

Table 10. Indirect effects via satisfaction

Indirect Path	β	95% CI	Result
TR → SAT → CI	.157	[.07, .27]	Significant
PU → SAT → CI	.221	[.12, .34]	Significant
PR → SAT → CI	−.097	[−.19, −.01]	Significant (small)
TR → SAT → PI	.133	[.06, .24]	Significant
PU → SAT → PI	.189	[.10, .31]	Significant
PR → SAT → PI	−.083	[−.17, −.01]	Significant (small)

Student satisfaction acts as a significant central mediator for the effects of trust (TR), perceived usefulness (PU), and perceived risk (PR) on continuance intention (CI) and the willingness to invest in personalized learning (WIPL). Notably, the PU → SAT → (CI/WIPL) pathway exhibits higher β coefficients. This suggests that perceived usefulness functions as the strongest predictor pathway in influencing student behavior.

The third research question of the study was stated as follows: “Do risk sensitivity (RS) and creative thinking/self-regulation (CT) moderate these relationships?” (H12–H13, moderation). The findings obtained through path and moderation analyses are presented in Table 11.

Table 11. Moderation results and simple slopes

Hypothesis	Interaction	β	t	p	Simple Slope Summary
H12	FEXP×RS → TR	.14	2.17	.031	RS +1 SS: FEXP→TR β=.40; RS −1 SS: β=.23
H12	FEXP×RS → PR	−.12	2.04	.042	RS +1 SS: FEXP→PR β=−.36; RS −1 SS: β=−.20
H13	PU×CT → SAT	.15	2.49	.013	CT +1 SS: PU→SAT β=.51; CT −1 SS: β=.32

When RS is high, the effect of the feature on trust becomes stronger, and the effect on risk becomes more negative. This indicates that individuals who are more sensitive to risk signals disproportionately benefit from uncertainty-reducing features such as video feedback. When CT is high, the slope of the PU → Satisfaction path significantly increases, suggesting that users with high tendencies in planning/self-monitoring and creative problem-solving better recognize the perceived value of the feature.

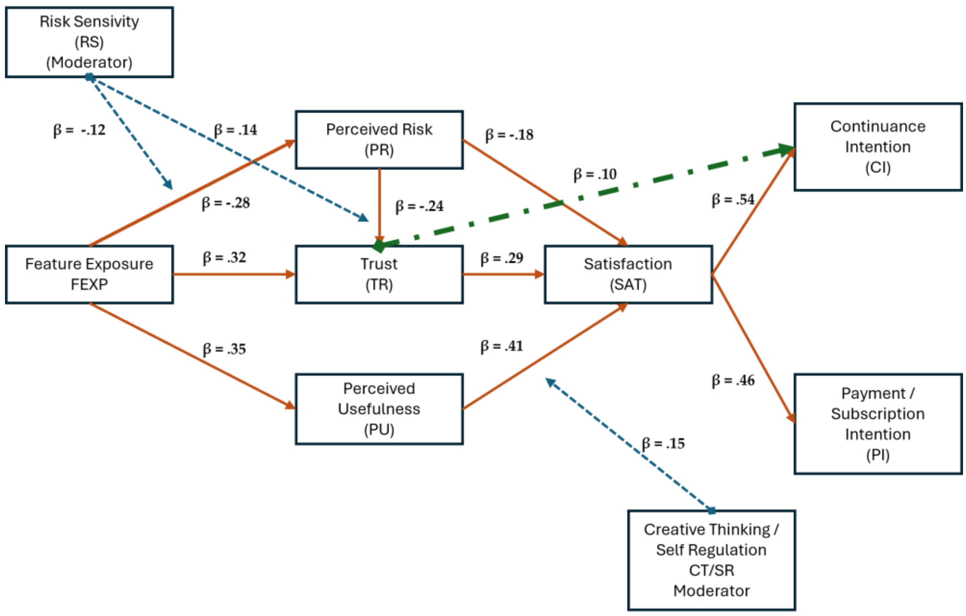

Figure 2. Research Model and Standardized Path Coefficients (N=88)

The structural model results (summarized in Figure 2) were further validated through PLSpredict, where the $Q^2_{predict}$ value for satisfaction (0.29) indicated moderate out-of-sample predictive power. The practical predictive capability was confirmed as the majority of target endogenous indicators (8 out of 12) exhibited lower RMSE values in PLS regression compared to the linear model. Common method variance was ruled out via Harman's single-factor test (31%) and inner VIF values below 2.25 across all constructs.

To assess group differences, MICOM and MGA procedures established partial measurement invariance. Path coefficient comparisons between the experimental and control groups revealed no significant differences ($p_{diff} > .05$), confirming the model's structural stability. Additionally, sensitivity analyses involving outlier adjustments and alternative imputations yielded consistent findings, reinforcing the model's overall robustness.

In summary, video-enabled feedback enhances student satisfaction by mitigating perceived risk and bolstering trust and perceived usefulness. Student satisfaction, as the central mediator, strongly predicts both continuance intention (CI) and the willingness to invest in personalized learning (WIPL). Furthermore, individual differences, namely virtual risk sensitivity and creative thinking/self-regulation, effectively moderate these pathways, aligning with TAM-ECM and trust–risk integration frameworks (Bhattacherjee, 2001; Pavlou, 2003). These findings suggest that strategic service design can significantly improve student retention and continuous engagement in EdTech platforms.

Discussion

The findings of this study suggest that the video-enabled feedback feature generates multidimensional effects on student experience and behavioral intentions within EdTech platforms. First, our results reveal that video-enabled feedback increases trust, reduces perceived risk, and enhances perceived usefulness (PU). This is consistent with similar mechanisms reported in previous studies in e-learning and mobile payment contexts. For example, in mobile wallet services, PU has been found to be the strongest predictor, while trust plays a critical supporting role (Tripathi, 2023). Similarly, studies focused on video applications have shown that trust and perceived usefulness enhance students' continuance intention (CI) (Zhu, Zhai, & Li, 2025).

Second, the cascading effects of trust (TR), perceived risk (PR), and perceived usefulness (PU) on student satisfaction (SAT), continuance intention (CI), and the willingness to invest in personalized learning (WIPL) were confirmed. Student satisfaction plays a central mediating role in these relationships, particularly serving as a mediator between trust, PU, and behavioral intentions (specifically, CI and WIPL). This finding aligns with research in the payment technologies literature, where user satisfaction has been identified as a factor that reshapes both trust and risk perceptions, ultimately determining continuance intention (Chen & Li, 2017; Yadav et al., 2024). In this context, the confirmed relationship between satisfaction and payment intention (PI) should be interpreted through the lens of Willingness to Invest in Personalized Learning (WIPL). This suggests that satisfied learners do not merely view the service as a financial transaction but as a valuable educational investment worthy of resource allocation to sustain a personalized feedback experience.

Third, the moderating role of individual differences—namely, virtual risk sensitivity (RS) and creative thinking and self-regulation (CT)—was analyzed. The findings show that students with high risk sensitivity experience the effects of perceived risk more strongly, while creative thinking and self-regulation abilities reinforce the positive effects of trust and PU perceptions. This result aligns with studies that emphasize the important role of user characteristics in technology adoption and continuance processes (Ha et al., 2023; Ansori & Nugroho, 2024).

In a similar vein, Kim et al. (2025) highlighted that beyond utilitarian benefits such as perceived usefulness, intrinsic motivations like perceived enjoyment can exert an even stronger influence on learners' behavioral intentions, especially in AI-assisted environments where user engagement plays a pivotal role in sustained adoption.

In conclusion, this study reveals that video-enabled feedback is not only a pedagogical tool but also an influential instructional design instrument encompassing psychological and behavioral dimensions. The integration of trust and risk dimensions into EdTech design appears to be decisive for fostering sustainable learner engagement and supporting the long-term viability of personalized learning environments.

Conclusions

This research demonstrates the multidimensional impact of video-enabled feedback on EdTech user experience. Findings reveal that trust, perceived risk, and perceived usefulness are fundamental in shaping user satisfaction, which subsequently drives both continuance intention and the Willingness to Invest in Personalized Learning (PI/WIPL). Thus, video feedback transcends its pedagogical role, acting as a strategic service design element that fosters engagement and sustainable revenue models. This transition from free usage to paid investment reflects a psychological shift where the perceived value of personalized interaction successfully outweighs inherent digital risks.

Theoretically, this study extends the TAM/UTAUT and ECM-ISC frameworks by integrating a robust trust–risk perspective. By clarifying the causal mechanisms through which video feedback reframes behavioral intentions, the research offers a more comprehensive model for technology adoption in EdTech. Methodologically, the use of a quasi-experimental design and PLS-SEM analysis ensures the internal validity and practical applicability of these causal inferences, contributing a rigorous empirical foundation to the literature.

Practically, EdTech developers should prioritize the trust-enhancing and risk-reducing capacities of video-enabled feedback. Enhancing platform trust and minimizing perceived risk are critical to strengthening learner satisfaction and investment intentions. Finally, future research should explore the generalizability of these findings across diverse cultural contexts and investigate the ethical and privacy dimensions of AI-supported video feedback tools through longitudinal designs.

Declarations

Funding: This research received no external funding.

Ethics Statements: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Necmettin Erbakan University, Social and Human Sciences Scientific Research Ethics Committee (protocol code 2023/558 meeting number 12; application number 16876; date of approval: 08/12/2023).

Conflicts of Interest: The authors declare no competing interests.

Informed Consent: Informed consent was obtained from all humans involved in the study.
Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

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