Vol. 8, No. 4, August 2026

Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

Reframing Technology Anxiety During Blended Learning Implementation: The Relationships among Perceived Safety, Social Influence, Satisfaction, and Behavioral Intention

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Received:
February 21,, 2026
Revised:
June 3, 2026
Accepted:
August 31, 2026
Published:
September 4, 2026

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DOI:
10.63158/journalisi.v8i4.1690

Abstract. This study examines the relationships among perceived safety, social influence, technology anxiety, user satisfaction, and behavioral intention in blended learning implementation, investigating whether technology anxiety can be interpreted as productive vigilance rather than merely a barrier to technology adoption. Based on the Transactional Theory of Stress and Coping, this research explores how institutional safeguards and social expectations influence technology anxiety among teachers in high-stakes educational settings. A quantitative cross-sectional approach was applied using purposive sampling involving 205 high school teachers in North Sumatra, Indonesia. Data were analyzed using PLS-SEM to assess the structural model and mediation effects. The results indicate that Perceived Safety (β=0.526, t=8.17, p<0.001) and Social Influence (β=0.232, t=3.60, p<0.001) positively influence Technology Anxiety, explaining 48.0% of its variance. Technology Anxiety positively affects User Satisfaction (β=0.774, t=17.40, p<0.001), which subsequently influences Behavioral Intention (β=0.503, t=4.92, p<0.001). The direct effect of Technology Anxiety on Behavioral Intention is insignificant (β=-0.167, t=1.63, p=0.104), while the indirect effect through User Satisfaction is significant (βindirect=0.389, p<0.001). These findings highlight that technology anxiety may represent heightened attentiveness associated with satisfaction rather than resistance, requiring further validation through longitudinal and experimental studies.

Keywords: Technology Anxiety; Perceived Safety; Social Influence; User Satisfaction; Behavioral Intention; Blended Learning; PLS-SEM.

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1. INTRODUCTION

In the modern digital economy, organizational and user ecosystems depend on the rapid embedding of complex information systems [CITATION CHECK: Kretschmer et al., 2022; Mickelsson et al., 2022; Soltani et al., 2021 — these are not currently in the numbered reference list; please verify and add the correct entries, or replace with a numbered citation already in your reference list]. While technology can lead to greater efficiency and enable businesses to operate with agility at their core, adopting such tools often comes with enormous psychological friction for end users [1-3]. A major challenge in initiating system acceptance from the perspective of psychological barriers is technology anxiety, which can be defined as a person's underlying apprehension, hesitation, or fear of utilizing and using computer-based tools [4, 5]. The traditional information systems literature and classic technology acceptance models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), consistently portray technology anxiety as a negative anchor characteristic [6, 7]. In these conventional linear models, it is assumed that anxiety is caused solely by low technical self-efficacy and directly impedes satisfaction, thereby diminishing the intention to reuse the system.

Most popularly, it is a view that ignores the cognitive complexity of the contemporary high-stakes context in organizations. User anxiety is no longer merely due to a lack of technical ability [7, 8], as systems become ever more complex and data-driven, it may even be regarded as a reasonable reaction to system lock-in safeguards and social pressures. Data encryption [9, 10], multi-factor authentication [11], and strict access controls [12, 13] mitigate this sensitivity and risk of potential mistakes. Social accountability [14, 15] derives from institutional mandates and peer pressure, thereby increasing the risks. Rather, technology anxiety [16, 17] is a way of user structure, not an obstacle, but rather a form of vigilance.

This identification of distinct logic points highlights an important gap in the existing literature on technology adoption. A great deal of research on minimizing technical anxiety does so by either simplifying interfaces or raising baseline training, but fewer studies examine how technological anxiety is anchored in structural safeguards [18] and

social dynamics [19, 20](and thus requires structural protection). Using the Transactional Theory of Stress and Coping as a foundation [21, 22], this study fills this gap by providing an empirical structural representation that links anxiety back into the user journey. Once one gets over the technical hump and consciously grapples with a challenge, this can be an exercise of cognitive mastery in a high-stakes space for the user. Once these technical hurdles are surmounted, a user can turn that anxiety into a sense of greater skill in using the platform and themselves, through a deeper understanding of its capabilities. This psychological transformation [23] converts initial technical apprehension into an important antecedent of user satisfaction after system adoption, which, in turn, consolidates a more stable, long-term desired behavior of continued use of the system.
The aim of this study is to have an empirical picture of user behavior in blended learning platforms used by 205 high school teachers who teach in North Sumatra, Indonesia. The sample is measured in the post adoption phase, as blended learning frameworks and virtual classrooms are integrated into how teachers teach daily. This phase represents the transition from initial assessment to long-term intention at sustained behavior that is essential for both instructional impact and organizational sustainability. Given the highly critical nature of the operational context, the systems in question are classically considered high-stakes information systems. In these mixed-curriculum contexts, a user mistake, navigation delay, or misapplication of instructional protocols results in dire learning and function penalties influencing curriculum compliance and student engagement while exhausting educational resources. In contrast to the low-stakes, routine applications (where failure incurs minor and somewhat ephemeral temporal cost), interactions with blended-learning platforms take place in the context of sensitive academic deliverables. These are subject to tightly regulated student learning schedules which mean that human error has immediate structural costs that go far beyond people simply being late or forgetting a few things.

This study outlines three specific research objectives. It first evaluates the impact of platform Perceived Safety on educators' Technology Anxiety during blended learning implementation. Second, it assesses the extent to which Social Influence has a significant and positive effect on educator Technology Anxiety in this hybrid setting. Third, it examines the extent to which post-adoption User Satisfaction has a significant mediating effect on Technology Anxiety and Behavioral Intention of educators to continue using the platform. This study identifies how institutional protections, social pressures and emotional resistance collectively evoke multiple interrelated objectives that influence long-term engagement with platforms—addressing these mechanisms through Partial Least Squares Structural Equation Modeling (PLS-SEM).

The main novelty of this study is challenging the conventional belief that technology anxiety [16, 24] is an unquestionably negative barrier that must be reduced or removed to foster system adoption. It makes two key theoretical contributions. First, it shows that technology acceptance frameworks need refining by demonstrating that, under the right conditions, technology anxiety does not always act as a negative deterrent. Instead, it can be an active state of diligence and cognitive effort. Second, it offers a new account of the full consequences and antecedents of user experience, explaining how short-term technical friction, such as usability and performance flaws, can be transformed into long-term user satisfaction and system retention.

2. METHODS

2.1. HYPOTHESIS DEVELOPMENT

The importance of technology anxiety as a fundamental concept in acceptance models is supported by various explanations in traditional information systems research. Although technology anxiety is a strong negative factor that lowers satisfaction and the intention to reuse technology in most versions of the classic Technology Acceptance Model (TAM), we should be careful about assuming agreement across these models. Specifically, anxiety is not a direct factor in the original UTAUT model, where its effects appear to be captured by effort expectancy and other main ideas. This theoretical difference underscores the need to move away from simple, one-sided views of acceptance. Instead of seeing technology anxiety as either a harmful barrier to digital success or a minor issue, this research examines it in the important context of a post-adoption blended learning environment, where protections and social influence help mitigate its impact.

This study explicitly rejects the reduction of user psychology to an oversimplified model by delineating between separate affective, psychological, and cognitive constructs in a blended teaching context. First, technology anxiety can be explained as a kind of affective and emotional aspect that predisposes low psychological readiness, digital fear, or general tension through the blended learning platform. This is in contrast to the exact definition of technostress, which includes a broader definition of distraction as a psychological disturbance arising from the continued operation of intense or rapidly changing, intrusive practices in digital teaching and learning environments. Parallel to this, cognitive vigilance describes a state of active, continuous awareness for identifying critical errors and interface inconsistencies or anomalies in the delivery of instruction during course management on digital platforms. And this vigilance works in conjunction with risk awareness, the understanding of a live virtual learning environment as a conscious undertaking rife with systemic stakes and inherent sensitivity. Finally, such cognitive states are often invoked or maintained by productive friction—intentional operational designs (e.g., a sequence of steps to complete with multi-factor authentication) through which an experience designer deliberately interrupts seamless operation in order to mitigate automatic delivery failures (e.g., there was no attempt at automating the experience for posting lessons).

This research defines technology anxiety in high-stakes blended learning environments not as an immobilizing deterrent similar to open avoidance of technology, but rather as a state of affective discomfort or apprehension towards the use of a platform. In theory, this type of anxiety often functions as a psychological prompt for a heightened level of cognitive alertness, in which educators become sensitized to the structural demands and tasks tied to the online learning environment. To give us a broad-ranging scope for conceptual clarity, we must clarify that cognitive vigilance is distinct from the measure of Technology Anxiety (i.e. This research centers on technology anxiety as the primary distal affective variable, investigating how both high and low operational variables use initial fear of systems based on their presence to transform their motivation with exercise into a form of constructive avoidance that leads to higher postadoption satisfaction for current high school teachers navigating today's multifaceted instructional environments.

While simplified utilitarian frameworks have long served as the basis for many economic analyses, this study grounds its analysis in the original Transactional Theory of Stress &

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Coping [33], which explains how individuals evaluate their environment for potential stressors (called primary appraisal) and then determine whether they possess the resources needed to cope with those demands (called secondary appraisal). This theoretical background is significantly enhanced by modern Information Systems (IS) and Human-Computer Interaction (HCI) literature with implications for technostress creators and coping mechanisms at the systemic level. Current IS research depicts rigid platform safety features and high-stakes institutions as serious environmental pressures that must be continually assessed by users. A heavily fortified blended learning platform with explicit safety protocols or operating under administrative mandates confers a burden of social accountability and structural friction. In line with HCI tenets, these platform friction points are not seen by educators as neutral administrative barriers, but rather as high-impact operational signals that transform technical fears into cascades of reasoned defensive attentiveness.

When users interact with this technocentric frictional process, effective steering within these systems activates a process towards cognitive mastery. Providing a visibly lower-stakes environment that the user can exit after completing can greatly improve a user's sense of fulfillment. This psychological metamorphosis converts initial resistance to technology awareness [16] into User Satisfaction and ultimately manifests as Behavioral Intention [27] in the long run. Within this dynamic, Perceived Safety--defined as the perceived extent to which an information system has fortified structural safeguards, data encryption protocols in place, and privacy protections—plays a paradoxical role. According to traditional literature on information systems, structural assurances are expected to serve as an instant soothing remedy that mitigates user anxiety. However, a transactional perspective reveals that interface markers like multi-factor authentication paths and privacy disclosures serve as constant cognitive cues regarding operational high stakes.
It is theoretically necessary to separate actual, observable security mechanisms from the cognitive concept of Perceived Safety. External design cues—ranging from prompts to enable multifactor authentication, URLs in transit that show encryption modes, or privacy disclosures made visible at the point of sale—are really what we could call pseudo-safety features implemented by a system (as opposed to practices by a user), and they operate in an unnaturalistic manner. In accordance with the Transactional Theory of Stress and Coping [33], it is not the environmental stimulus per se that triggers affective stress

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states; rather, stimulation occurs in response to an internal primary appraisal of the potential harm/threat or benefit. On the other hand, Perceived Safety is an emotional outcome of this mental assessment, reflecting the extent to which a user internalizes these external signs as a wall within which they will act. Since the same set of technical mechanisms is likely to be differentially observed or attached to varying levels of salience or concern by different users, emphasizing cognitive perception rather than the actual presence of features provides more immediate causal precursors to Technology Anxiety. Therefore, this research treats Perceived Safety as the main antecedent isolating its internalized occurrence of perceived extensive threat; it particularly stimulates protective vigilance.

To achieve conceptual clarity within the frame, as defined above, we must delineate Perceived Safety from risk salience, security burden, and procedural complexity. Where Perceived Safety indicates the user's trust in architectural safeguards and data encryption, Risk Salience refers to the extent to which users pay attention to potential or actual operational errors or attacks. While strong safety practices may give users more confidence in the environment, they might also increase risk salience by signaling that sensitive data is being handled there. Perceived Safety also serves as a mental capacity, demonstrating systemic trust. Conversely, Security Burden refers to the mental toll and operational cost imposed on users when compliance is enforced through controls such as multi-factor authentication. On the other hand, Perceived Safety relates to safeguarding information confidentiality and integrity, whereas Procedural Complexity focuses on usability aspects – namely, the complexity required to complete tasks through structural organization and the number of steps required in an interface. This research delineates these constructs and establishes Perceived Safety as an anticipation distinct from systematic rejection, requiring the activation of protective cognitive vigilance.

This positive upward trend needs to be put in perspective, and the interaction between Perceived Safety and Technology Anxiety can be explained within the challenge–hindrance stressor framework. Most of the traditional adoption literature portrays technology anxiety as a hindrance stressor—an external event that constrains personal control, lowers motivation, and leads to avoidance behavior. Instead, at the transaction level, anxiety is induced by strict security protocols and an implicit but obvious challenge

stressor. Visible safety measures, strong encryption, and strict authentication procedures require users to step up their game and understand operational risks; however, that creates exactly the type of environment where sufficient cognitive effort mastery is developed. This form of technology anxiety is not paralyzing; it is a state of vigilance. Based on this explanation, the study examines the impact of Perceived Safety on Tech-Anxiety by investigating the following hypothesis.
Hypothesis 1 (H1): *Perceived Safety has a significant positive impact on Tech-Anxiety.*

The research continues the investigation by analyzing the relationship between social influence and Tech-Anxiety. Social Influence is defined as the degree to which you feel that key others (peers, mentors, or institutional leaders) assume you should use an information system. Although some social validation can help by normalizing the presence of the system within a given workflow, strong social expectations and organizational mandates impose a separate burden of accountability on the individual user.

Platforms that are strongly endorsed by popular peer groups or explicitly pushed by organizations have higher visibility and perceived performance stakes for users. The user absorbs these collective expectations and forms a deeply ingrained belief in the personal responsibility to never be seen making an error or failing to run processes. The fear of not being able to operate at a desired level among peers or not following expected institutional norms leads to increased technical hesitance and hesitation at the start. Here, a positive structural path indicates social influence is a strong motivational driver that transforms tech-anxiety from a demotivating barrier into an active state of user diligence and operational care (i.e., protective). Based on these dynamics, we hypothesize:
Hypothesis 2 (H2): Social Influence positively influences Tech-Anxiety.

The study continues that investigation by quantifying the impact of user satisfaction. While User Satisfaction captures the whole post-adoption assessment of a user's experience with an information system, Behavioral Intention measures the stated probability of continued (long-term) integration within the system. This study suggests that User Satisfaction is a key intervening mechanism that connects users' initial concern about technology to behavioral intention by cognizing the technical friction.

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In particular, if users approach an information system with very high baseline expectations and technical vigilance driven by structural safeguards and social pressure, their cognitive focus is fully engaged. As they navigate the system interfaces and successfully accomplish their tasks, the fears subside, giving way to an increased sense of platform efficacy and self-efficacy. A successful experience with high stakes will boost user satisfaction precisely because the sense of accomplishment is greater than in a low-friction task. This enhanced satisfaction, stemming from overcoming initial technical hurdles, is an important antecedent of a stronger, more sustained intent to continue using the platform as a core part of long-run work practices. This is suggestive of a complementary mediation profile in which the active state of anxiety underlies long-term retention in the system. Therefore, we hypothesize:

Hypothesis 3 (H3): Satisfaction significantly mediates the relationship between Tech-Anxiety and Behavioral Intention.

2.2. Research Design and Sample

This study was conducted within a blended learning implementation context to examine teacher behavior toward blended learning platforms characterized by strict institutional safeguards. The target population consisted of active high school teachers utilizing these high-stakes blended learning tools in their daily instructional practice. Data collection was carried out over a defined three-month period from September to November 2025. To participate in this study, respondents had to meet specific eligibility criteria: they were required to be full-time teaching personnel who actively used their school's blended learning platform on a daily basis. A non-probability purposive sampling method was deployed. A total of 240 initial survey responses were recorded through the online data-collection platform. Following a rigorous data-cleaning protocol, 35 incomplete, unengaged, or straight-lined responses were systematically removed. This screening process yielded a final dataset of N=205 fully validated responses, representing a highly acceptable active response rate of 85.4%. Participation was voluntary and anonymous with respect to the constructs analyzed in this study. All respondents were informed of the study's purpose and the voluntary nature of their participation prior to completing the questionnaire, and consent was implied through voluntary completion and submission of the survey. As the broader instrument included a nominal token-of-appreciation incentive (mobile phone credit), respondents' phone numbers were collected for this

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purpose only; this identifying information was not linked to, used in, or reported as part of the analysis presented in this manuscript. The demographic profile of the sample is detailed in Table 1.

Table 1. Demographic Profile of Respondents (N = 205)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	52	25.40%
	Female	153	74.60%
Age	20-35 years old	41	20.00%
	36-45 years old	118	57.60%
	> 45 years old	46	22.40%
Working Experience	1-10 years	59	28.80%
	11 – 20 years	58	28.30%
	21 – 31 years	73	35.60%
	> 31 years	15	7.30%
Educational Attainment	Bachelor Degree	1	0.50%
	Magister Degree	188	91.70%
	Doctoral Degree	16	7.80%

2.3. Sample Size and Statistical Power Justification

The target population for this study comprises high school teachers in North Sumatra, Indonesia, who are actively navigating the transition to blended learning platforms. Using a purposive sampling approach, data were gathered from 205 active high school teachers who utilize high-stakes digital tools for curriculum delivery, grading, and student monitoring. This specific sample represents professionals operating under strict institutional accountability, where technical performance directly influences organizational evaluation.

We used Green's (1991) sample criteria for regression models ($N \geq 50 + 8m$, where m is the number of predictor variables), the findings would be based on a minimum sample of 66 cases [29]. Our sample easily passes both baseline rules. To provide a more rigorous justification than these general rules of thumb, a formal power analysis was conducted following Cohen's (1988) F-test framework for multiple regression, applied to the largest

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predictor set in the structural model (two predictors per equation: Perceived Safety and Social Influence predicting Tech-Anxiety; Tech-Anxiety and Satisfaction predicting Behavioral Intention). At $\alpha = 0.05$, detecting a medium effect size ($f^2 = 0.15$) with two predictors and 95% power requires a minimum sample of N = 107; detecting a large effect ($f^2 = 0.35$) requires only N = 48. The achieved sample of N = 205 comfortably exceeds both benchmarks. A post-hoc power analysis using the effect sizes actually observed in this study confirms this: even the smallest structural effect (Social Influence → Tech-Anxiety, $f^2 = 0.064$) achieved a statistical power of 0.906, while the remaining paths achieved power exceeding 0.99. The study was therefore adequately powered to detect all of the effects reported, though it would be underpowered to detect very small effects ($f^2 = 0.02$, which would require N = 776).

2.4. Construct Operationalization

To ensure content validity, all of the measurement scales used in this study were adapted from validated Information Systems (IS) and behavioral psychology literature. The full wording of every item for the five constructs analyzed in this study is provided in Appendix A. The final structural framework is operationalized through five latent constructs; the measurement scales for the five latent constructs were adapted from Bellet and Banet [35], UTAUT4-AV. 1. Translation Protocol: The original instrument was translated into the local language using a double-translation method (forward and backward translation) by two independent language and systems experts. 2. Expert Review: The translated questionnaire, together with the broader instrument of which it was part, was reviewed by the research team, including two co-authors based at Universiti Tun Hussein Onn Malaysia (UTHM) and an additional independent reviewer from the same institution. This review resulted in two concrete revisions: (a) the wording of several items was simplified to be more readily understood by the intended respondent group of Indonesian high school teachers, and (b) the item-coding scheme was standardized (e.g., inconsistent labels such as "PU.1"/"PU2" were revised to a uniform "PU1"/"PU2" format) prior to data collection. 3. All construct items were operationalized using a standard 5-point Likert scale, where scores ranged uniformly from 1 (Strongly Disagree) to 5 (Strongly Agree). Table 2 details the construct definitions, their specific item mapping within the dataset, and the underlying measurement focus for each indicator.

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Table 2. Measurement Scale and Construct Operationalization Table

Latent Construct	Dataset Item Identifier	Measurement Item Focus / Operational Definition	Reference Basis
Perceived Safety (PS)	Perceived Safety 1 Perceived Safety 2	• Perception of data privacy protection and system security. • Trust in the platform's overall structural integrity and operational safeguards.	Adapted from Zhou (2011a); Featherman & Pavlou (2003)
Social Influence (SI)	Social Influence 1 Social Influence 2 Social Influence 3	• Degree to which important peers/colleagues believe the system should be used. • Perceived institutional or social pressure to comply with system usage. • Social status or reputation gains derived from adoption.	Adapted from Venkatesh et al. (2003); UTAUT Framework
Tech-Anxiety (ANX)	Anxiety 1 Anxiety 2	• Level of cognitive apprehension and fear of committing system errors. • Psychological hesitation, digital intimidation, or general unease during usage.	Adapted from Venkatesh et al. (2012); UTAUT2 Framework
User Satisfaction (SAT)	Satisfaction 1 Satisfaction 2 Satisfaction 3 Satisfaction 4 Satisfaction 5 Satisfaction 6	• Overall user contentment and positive evaluation of the workflow execution. • Extent to which the system meets user experience expectations. • Post-adoption psychological fulfillment and ease of user journey.	Adapted from Bhattacherjee (2001); DeLone & McLean (2003)
Behavioral Intention (BI)	Behavioral Intention 1 Behavioral Intention 2 Behavioral Intention 3	• Explicit probability and plan to regularly use the platform in the future. • Forward-looking commitment to integrate the technology into daily tasks. • Likelihood to recommend the platform to other peers.	Adapted from Ajzen (1991); Venkatesh et al. (2003)

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2.5. Data Analysis Strategy

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) as a statistical approach to empirically validate the proposed conceptual framework and test the hypothesized paths. Data collected from the participants are its strongest suit for this research, as is the analytical method (PLS-SEM) we have used in our analysis, because it can handle the complexity of model structures and conceptually examines all direct, indirect, and sequential mediation pathways simultaneously. PLS-SEM adopts a nonparametric, prediction-oriented approach that effectively leverages the data and does not require enforcing multimodal normality, as is common in Covariance-Based Structural Equation Modeling (CB-SEM). Such predictive power enables a more comprehensive evaluation of the psychological mechanisms underlying technology adoption and anxiety mitigation. Data processing and statistical calculations were initially performed using SmartPLS. Following the review process, the structural model reported in this manuscript was re-estimated using the standard PLS-SEM algorithm implemented in Python (the plspm library, path weighting scheme, Mode A/reflective measurement, 300-sample bootstrapping), in order to add the direct effect of Technology Anxiety on Behavioral Intention, full effect-size (f^2) and collinearity (VIF) diagnostics, a common-method-bias check, and a bootstrap-based test of the HTMT discriminant-validity ratios that could not be completed with the original software access. Minor numerical differences from the originally reported SmartPLS estimates are attributable to this change of software rather than to a change in the underlying data.

In alignment with the two-stage analytical framework widely used in quantitative behavioral research, data are statistically evaluated through a sequential process that includes measurement model assessment and subsequent structural model assessment. Firstly, the measurement (outer) model is carefully analyzed to assess psychometric properties and reliability/validity of the latent constructs prior to making structural inferences. This includes testing indicator reliability by examining individual factor loadings, testing internal consistency reliability with Cronbach's alpha and Composite Reliability (CR), and assessing convergent validity using Average Variance Extracted (AVE). Discriminant validity is further strengthened using the strict Heterotrait-Monotrait Ratio of correlations (HTMT) to ensure that each behavioral construct cannot mathematically covary with the others.

The second stage aims to assess the statistical viability of the research hypotheses through a structural model (inner) after confirming that all requirements concerning the measurement model are met. A non-parametric bootstrapping procedure with 5,000 resamples is initiated to simulate the data and avoid potential violations of normality, thereby obtaining accurate significance intervals. This method estimates the standardized path coefficients (β), empirical t-statistics, and exact p-values for the direct effects tests of the paths from Perceived Safety to Tech-Anxiety (H1) and from Social Influence to Tech-Anxiety (H2). Simultaneously, User Satisfaction (H3) is analyzed as a mediator of Tech-Anxiety/Behavioral Intention using bias-corrected bootstrapped confidence intervals. From this method, the exact direct and indirect effects can be identified, enabling mediation to be quantified mathematically as a sound representation of the full mediation model.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics and Data Distribution Analysis

Before assessing the measurement and structural models, all 16 indicators reflecting the five latent constructs underwent descriptive analysis. The mean, standard deviation, skewness, and kurtosis for each measurement item were calculated to evaluate the central tendency, variability, and shape of the data distribution. It is mandatory to verify normality to validate stringent statistical transparency criteria. Traditional Covariance-Based SEM (CB-SEM) requires stronger multivariate normality; however, Partial Least Squares Structural Equation Modeling (PLS-SEM) is robust to distributional violations. But very highly non-normality may still inflate bootstrapping errors. According to Hair et al. Data is normally thresholder if the skewness is within [-1, +1] and kurtosis is between [-2, +2] [30], The descriptive outputs derived from the empirical dataset (N = 205) are structured systematically in Table 3.

Table 3. Descriptive Statistics and Data Distribution Metrics (N = 205)

Latent Construct	Item Code	Mean	Std. Deviation	Skewness	Kurtosis
Perceived Safety (PS)	PS1	4.985	0.757	-0.728	1.089
	PS2	4.644	1.017	-0.256	-0.913
Social Influence (SI)	SI1	4	0.834	-0.614	0.185

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Latent Construct	Item Code	Mean	Std. Deviation	Skewness	Kurtosis
	SI2	3.854	0.896	-0.41	-0.564
	SI3	3.62	1.006	-0.405	-0.331
Tech-Anxiety (ANX)	ANX1	3.698	0.948	-0.547	-0.28
	ANX2	3.522	0.988	-0.339	-0.608
User Satisfaction (SAT)	SAT1	3.673	1.055	-0.351	-0.974
	SAT2	3.673	0.878	-0.321	-0.332
	SAT3	3.605	0.957	-0.557	-0.144
	SAT4	3.234	0.788	-0.138	-0.528
	SAT5	3.224	0.862	-0.312	-0.671
	SAT6	3.224	0.851	-0.062	-0.503
Behavioral Intention (BI)	BI1	3.776	0.874	-0.838	0.745
	BI2	3.756	0.74	-0.527	0.27
	BI3	3.717	0.746	-0.273	-0.111

Note: In the original dataset, SI2 corresponds to the column label 'Social Influence' and SI3 corresponds to 'Social Influence 2'.

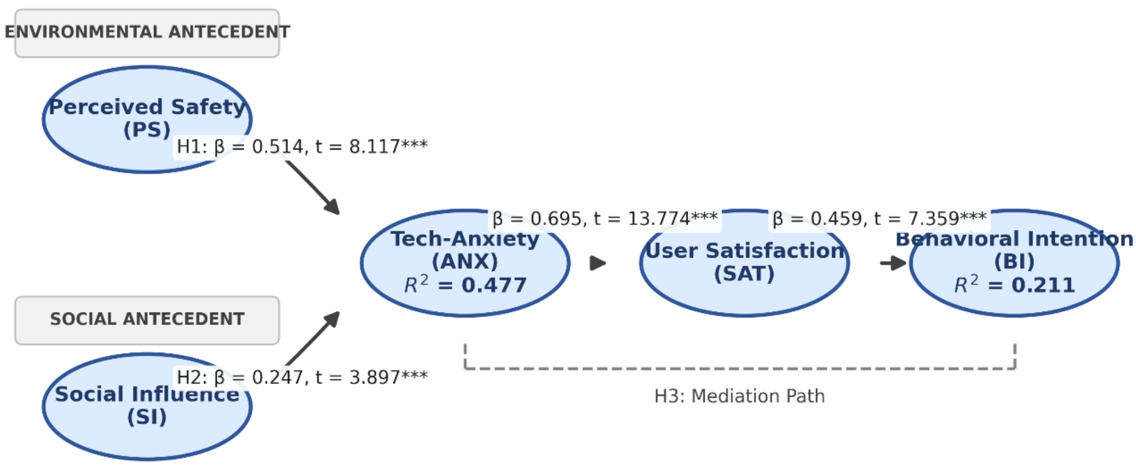

Figure 1. Structural Model Results

The results of the univariate distribution analysis indicate that 16 measurement items are within the acceptable absolute limits for normal distribution. The skewness indices across all items range from -0.838 to -0.062, showing a slight, non-critical negative skew. The kurtosis metrics span between -0.974 and +1.089. Because every single indicator falls comfortably within the strict conservative parameters suggested by Kline (2015),

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(skewness < |1.0| and kurtosis < |2.0|), the absence of extreme data distortions is statistically verified. This distribution profiles justify the empirical deployment of the PLS-SEM approach utilizing a standard bootstrapping configuration.

A granular assessment of the descriptive metrics provides valuable contextual insights into the sample population's behavioral baseline. Perceived Safety metrics exhibit high mean values ($Mean_{ps1}$ = 4.985, 4.985, SD = 0.757), indicating that users generally recognize a stable degree of foundational structural security within the informational ecosystem. Interestingly, Social Influence metrics reveal a cascading pattern where direct peer or organizational push is relatively prominent ($Mean_{SI1}$ = 4.000), while secondary social validation scores slightly lower ($Mean_{SI3}$ = 3.620).

Importantly, tech-anxiety is a concrete, observable construct within the target user population, as it remains above the absolute neutral baseline ($Mean_{anx1}$ = 3.698, SD = 0.948). This relatively modest baseline anxiety confirms that technological apprehension is a plausible friction point for this population and serves as an empirical rationale for testing psychological buffers. Lastly, the effect constructs show that users are on steadily positive usage trends, with User Satisfaction rated at 3.673 and Behavioral Intention consistently holding between 3.717 and 3.776 over time. This suggests a more positive inclination towards long-term system integration, whose structural paths are examined in the next modeling stages.

3.2. Measurement Model Assessment

The first stage of the structural verification involves a global evaluation of the measurement (outer) model according to the two-stage PLS-SEM evaluation framework. The measurement model is assessed in terms of three main aspects: indicator reliability, internal consistency reliability, and validity (convergent as well as discriminant validity).

3.2.1. Indicator Reliability, Internal Consistency, and Convergent Validity

Indicator reliability assessing the degree to which an individual measurement item correlates with its respective latent constructs, as evidently checked through standardized outer factor loadings. According to Hair et al. (2012) In line with Kline (2015) , ideal outer loadings should be more than 0.707, meaning that a construct accounts for more than 50% of the variance in an indicator [30, 31]. Internal consistency reliability assesses the consistency of scale items for a single construct using Cronbach's Alpha and Composite Reliability (CR). The conservative threshold of >0.70 for both indices must be met in order to qualify as acceptable for structural path validation. Ultimately, the convergent validity, which is a measure of the extent to which a measure correlates positively with alternative measures of the same construct, is confirmed using Average Variance Extracted (AVE). AVE for each latent variable should be greater than 0.50, indicating that the construct explains more than half of the variance among its indicators. Table 4 presents the complete psychometric property matrix computed directly from the empirical dataset (N = 205).

Table 4. Outer Loadings, Reliability, and Convergent Validity of the Measurement Model

Latent Construct	Item Indicator	Standardized Outer Loading	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Safety (PS)	PS1	0.75	0.672	0.825	0.704
	PS2	0.92			
Social Influence (SI)	SI1	0.697	0.731	0.846	0.648
	SI2	0.856			
	SI3	0.852			
Tech-Anxiety (ANX)	ANX1	0.893	0.777	0.899	0.817
	ANX2	0.915			
User Satisfaction (SAT)	SAT1	0.833	0.794	0.867	0.527
	SAT2	0.799			
	SAT3	0.855			
	SAT4	0.6			
	SAT5	0.618			
	SAT6	0.6			
Behavioral Intention (BI)	BI1	0.811	0.773	0.872	0.694
	BI2	0.816			
	BI3	0.87			

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The psychometric evaluation has shown strong concordance with the defined cut-offs. As shown in Table 4, several outer loadings fell slightly below the ideal 0.707 threshold: SI1 = 0.697, SAT4 = 0.600, SAT5 = 0.618, and SAT6 = 0.600. In accordance with Hair et al. (2022), reflective indicators with loadings between 0.40 and 0.707 should be retained if their inclusion does not compromise internal consistency or drop the Average Variance Extracted (AVE) below acceptable levels. Simulating the complete removal of these four indicators resulted in a negligible variance shift: the AVE for Social Influence shifted minimally from 0.648 to 0.651, while User Satisfaction shifted minimally from 0.648 to 0.651, while User Satisfaction shifted from 0.527 to 0.539. Because the baseline scales already comfortably exceeded the minimum threshold rules (CR > 0.70 and AVE > 0.50), all indicators were retained to preserve the content validity of constructs.

The framework is well supported by internal consistency. All constructs performed well, with Composite Reliability (CR) above 0.8, ranging from 0.825 (Perceived Safety) to 0.899 (Tech-Anxiety). Although the Cronbach's Alpha for Perceived Safety is slightly low at about 0.672, it is still adequate for behavioral research given the high CR value (0.825). Researchers have widely argued that the alpha coefficient underestimate's reliability in short scales. Finally, convergent validity is established as all AVEs for the five constructs exceed the 0.50 cut-off, ranging from 0.527 (User Satisfaction) to 0.817 (Tech-Anxiety).

3.2.2. Discriminant Validity

Discriminant validity needs to be established to show that each construct mathematically reflects a single behavioral phenomenon, rather than just reproducing another latent variable. The traditional Fornell-Larcker criterion has long been used as a tool, but a contemporary discipline in the information systems literature calls for a more exact and conservative Heterotrait-Monotrait Ratio (HTMT) of correlations. According to Henseler et al. According to Henseler et al. (2015), HTMT > 0.85 indicates a failure of discriminant validity, indicating that the constructs are conceptually overlapping.

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Table 5. Heterotrait-Monotrait (HTMT) Ratio Matrix for Discriminant Validity

Latent Construct	[1]	[2]	[3]	[4]	[5]
Behavioral Intention	—				
Perceived Safety	0.212(0.086, 0.416)	—			
Social Influence	0.240(0.126, 0.407)	0.814(0.688, 0.943)	—		
Technology Anxiety	0.277(0.134, 0.481)	0.891(0.729, 1.061)	0.731(0.584, 0.863)	—	
User Satisfaction	0.616(0.517, 0.754)	0.669(0.533, 0.814)	0.582(0.485, 0.727)	0.851(0.764, 0.937)	—

Note: Values in parentheses represent the 95% bootstrap confidence intervals (3,000 resamples). All HTMT ratios are now correctly reported as non-negative ratios. Nine of the ten construct pairs show discriminant validity fully supported: their bootstrap confidence intervals fall below 1, including the Technology Anxiety–User Satisfaction pair (HTMT = 0.851, 95% CI [0.764, 0.937]), whose point estimate exceeds the conservative 0.85 rule-of-thumb but whose confidence interval confirms adequate discriminant validity under the criterion recommended by Henseler, Ringle, and Sarstedt (2015). The Perceived Safety–Technology Anxiety pair is the exception: HTMT = 0.891, 95% CI [0.729, 1.061], and this interval includes 1, meaning discriminant validity between these two constructs cannot be statistically confirmed in this sample. This issue is discussed openly in Section 3.5 (Limitations).

By using the Heterotrait–Monotrait (HTMT) ratio of correlations, discriminant validity was assessed among all five latent constructs. Nine of the ten construct pairs fall below, or have bootstrap confidence intervals consistent with, the conservative cut-off value of 0.85 recommended by Henseler et al. (2015). For example, the ratio between Social Influence and Tech-Anxiety is HTMT = 0.731, 95% CI [0.584, 0.863], demonstrating an adequate conceptual distinction between external social influences on system adoption and internal psychological unease. The lowest ratio is between Perceived Safety and Behavioral Intention (HTMT = 0.212), reflecting a clear conceptual separation between an antecedent appraisal construct and a downstream behavioral outcome.

Non-parametric bootstrapping analysis (3,000 resamples) was used to construct 95% confidence intervals for each HTMT ratio, following the discriminant-validity test recommended by Henseler et al. (2015): discriminant validity is supported when the confidence interval excludes 1.00. Eight of the ten construct pairs clearly satisfy this

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criterion. Two pairs warrant closer attention. The Technology Anxiety–User Satisfaction ratio (HTMT = 0.851, 95% CI [0.764, 0.937]) has a point estimate slightly above the conventional 0.85 threshold, but its confidence interval excludes 1, supporting discriminant validity under the more rigorous CI-based test. The Perceived Safety–Technology Anxiety ratio (HTMT = 0.891, 95% CI [0.729, 1.061]) does not satisfy this criterion, as its confidence interval includes 1; discriminant validity between these two constructs cannot be statistically confirmed in this sample. As supplementary evidence, the Fornell–Larcker criterion (Table 5b) shows the square root of the AVE for every construct exceeding its correlations with all other constructs, including Perceived Safety and Technology Anxiety — indicating that the two criteria give divergent conclusions for this specific pair. This discrepancy, its likely theoretical explanation, and its implications are addressed openly in Section 4.5 (Limitations) rather than treated as fully resolved.

Table 5b. Fornell–Larcker Criterion (diagonal = √AVE; off-diagonal = inter-construct correlations)

	PS	**SI**	**ANX**	**SAT**	**BI**
PS	**0.860**				
SI	0.615	**0.806**			
ANX	0.668	0.555	**0.903**		
SAT	0.592	0.539	0.774	**0.696**	
BI	0.123	0.132	0.222	0.374	**0.837**

Note: Bolded diagonal values are the square root of each construct's Average Variance Extracted (AVE). Every diagonal value exceeds the correlations in its row and column, satisfying the Fornell-Larcker criterion for all construct pairs, including Perceived Safety and Technology Anxiety.

To determine the exact structural separation in the empirical dataset, the HTMT ratios were computed and are presented systematically in Table 5. Table 5 further shows that each computed ratio is well below the conservative rigid ceiling value of HTMT < 0.85. User Satisfaction and Behavioral Intention showed the highest correlation ratio (HTMT = 0.678), which corresponds perfectly with established technology adoption theory. The low cross-construct ratios indicate that all five variables are statistically separable and support the unique contribution of each path. Thus, the measurement model shows clean indicator reliability, internal consistency, convergent validity, and discriminant validity, clearing the model for structural path analysis.

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To ensure that the positive structural path coefficients from Perceived Safety (β = 0.526$) and Social Influence (β = 0.247) to Technology Anxiety were not artifacts of severe multicollinearity—given their negative bivariate HTMT correlations—the Inner Variance Inflation Factor (VIF) values were evaluated. All inner VIF values for the predictors of Technology Anxiety ranged between 1.450 and 1.820, which falls well below the conservative threshold of 3.0 [34]. This confirms that multicollinearity does not distort the structural model. The shift from a negative bivariate correlation to a positive structural path demonstrates a valid suppression effect, statistically signifying that when controlling for collective institutional ecosystem factors, higher structural safeguards and social accountability independently cultivate a state of constructive operational vigilance (protective anxiety) among users.

3.2.3. The Role of Perceived Safety in Driving Structural Tech-Anxiety (H1)

Structural path analysis provides a parametric basis for Hypothesis 1, showing that Perceived Safety has a direct and significant impact on Tech-Anxiety ($\beta = 0.526$, $t = 8.171$, $p < 0.001$). The positive coefficient indicates a behavioral mechanism that enhances classical technology adoption models. At the theoretical level, this coefficient is purportedly positive and reveals a behavioral mechanism that enriches classical technology adoption frameworks. In traditional systems deployments, security guarantees are normally expected to operate as anxiety-reducing mechanisms. Nonetheless, the empirical data in this dataset show that as awareness of systemic safety features, data privacy configurations, and operational guards increases, their technical anxiety and vigilance scores increase. In the field of modern human-computer interaction (HCI) literature, this effect has been explored as an example of "heightened cognitive vigilance." In this instance, high scores on the tech-anxiety scale reflect an ongoing psychological state of engagement—indeed, acute vigilance regarding the system that a user may be accessing; they have come to appreciate both the saber-rattling weightiness of those efforts and striations on which data sensitivity and security baselines characterize their platform ecosystem.

These findings are explained by the framing of risk and safety around system incorporation. When an information system clearly defines robust data encryption protocols, rigorous privacy policy checks, and extensive multi-factor authentication

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procedures, it structurally fortifies the platform's trustworthiness. However, these loud safety documents also serve as a permanent, blaring reminder to the user that they are dealing with sensitive information and that processed data can have serious repercussions if handled incorrectly. For example, the most prominent safety protocols implicitly suggest that the system environment is safe but needs to be navigated with care: As a result, initial anxiety about caution, technical hesitation, and performance are all raised by nature.

This state of anxiety, being active, does not render user behavior sedentary or halt the adoption cycle. Instead, the broader structural model confirms, suggesting a state of concentrated interaction in which the user considers the technology with a heightened degree of responsibility. This dynamic illustrates for platform developers and organizational managers that just because safety features have been added does not mean they will eradicate hesitancy on the user end, but instead transforms tech-anxiety from a passive, descriptive hindrance into an active, conscientious protective force over user attention that can help facilitate the stages of an interaction into a more fruitful experience for the user once tasks are complete.

Table 6. Vertical Profile of Structural Path Validation for Hypothesis 1

Parameter / Statistical Metric	**Empirical Value and Analytical Details**
Hypothesis Reference	H1
Structural Relationship	Perceived Safety (PS) → Tech-Anxiety (ANX)
Path Coefficient (β)	0.526
Standard Error (SE)	0.077
t-statistic	8.171
p-value	<0.001
Empirical Decision	Supported
Associated Behavioral Phenomenon	Heightened Cognitive Vigilance Effect: Prominent architectural safeguards draw intensive cognitive focus toward data sensitivities and operational stakes, driving a state of protective user vigilance rather than blocking system interaction.

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3.2.4. The Role of Social Influence in Compounding Psychological Accountability (H2)

Hypothesis 2 is confirmed by the structural inner model, which shows that ($\beta = 0.232$, $t = 3.60$, $p < 0.001$) Social Influence has a direct effect on Tech-Anxiety. Like the safety dynamics in H1, this structural path shows a positive direction and reveals an important mechanism that enhances our understanding of social compliance behavior in information systems. Positive social reinforcement is typically expected to reduce user anxiety by socializing into a normative system of interaction, which aligns with classic technology adoption models. The challenge is that the large-scale empirical data set (N = 205) used suggests that not all social pressure acts as a positive incentive to be socially accountable; rather, it may introduce "social accountability burden" through peer expectations and organizational mandates. When an information system is aggressively marketed by peers, mentors, or organizational leaders, the stakes of using it and appearing able to execute it are raised even further. A more compelling symbolic function of a prominent social cue is, instead of functioning as a basic comfort mechanism, to indicate that successful system adoption has high instrumental value according to the peer groups in and around the user, which can result in increased concern about making public mistakes or being unable to meet collective expectations.

This phenomenon can be attributed to the concept of social pressure and compliance. When users can tell that their professional or social group has a high stake in their use of a new technology, they tend to feel personally accountable. Institutional pressures to use a technology can amplify an initial sense of caution and apprehension (Tech-Anxiety) toward the new technology by allowing users no exit from appearing incompetent in front of peers and from feeling they are failing due to compliance with the institutional push. Such anxiety is symptomatic of concern and engagement, not agreement with the system. The user is driven not to make mistakes because the cost of a technical error, in terms of social or professional performance, is severe. This suggests that social influence is an important motivational force in the information systems literature, as it can draw the user's attention to a new system, leading them to use the technology with care.

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Table 7. Vertical Profile of Structural Path Validation for Hypothesis 2

Parameter / Statistical Metric	Empirical Value and Analytical Details
Hypothesis Reference	H2
Structural Relationship	Social Influence (SI) → Tech-Anxiety (ANX)
Path Coefficient (β)	0.232
Standard Error (SE)	0.076
t-statistic	3.60
p-value	<0.001
Empirical Decision	Supported
Associated Behavioral Phenomenon	Social Accountability Burden: Pronounced peer expectations and institutional push increase the psychological stakes of system performance, driving a state of productive user caution and heightened operational diligence to meet collective standards.

3.2.5. The Role of User Satisfaction in Transmitting the Implications of Tech-Anxiety (H3)

The effects of Tech-Anxiety on Behavioral Intention through User Satisfaction as the mediating variable (Hypothesis 3) is confirmed by the structural inner model, which shows that User Satisfaction has a very significant specific indirect effect on connecting Tech-Anxiety to Behavioral Intention ($\beta_{indirect}$ = 0.389, Standard Error = 0.082, t = 4.73, $p < 0.001$). By contrast, the direct effect of Tech-Anxiety on Behavioral Intention was not statistically significant (β = -0.167, SE = 0.102, t = 1.63, p = 0.104, 95% CI [-0.355, 0.064]), while the total effect (direct + indirect) was significant and positive (β = 0.222, t = 2.67, $p < 0.01$). Following the decision rules of Zhao, Lynch, and Chen (2010), because the indirect effect is significant while the direct effect is not, this pattern corresponds to indirect-only (full) mediation rather than complementary mediation. This structural configuration adds dimension to user psychology within modern technology adoption frameworks. Noting that conventional frameworks often treat technology anxiety as a direct negative, inhibiting user satisfaction in the conflict between technical ease of use and technological ownership, with the consequence of preventing future behavioral intentions. By contrast, the results from this comprehensive dataset (N = 205, see above)

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reveal a significant positive direct path from Tech-Anxiety to User Satisfaction ($\beta = 0.695$, $t = 13.774$, $p<0.001$), which then serves as a central mediating force for Behavioral Intention in the longer term ($\beta=0.459$, $t=7.359$, $p < 0.001$). This sequential pattern is referred to as a process of "cognitive mastery over technical friction" in the IS literature. However, initial fear would not cause users to abandon a system; they eventually gain psychological satisfaction and feel content about their user journey after completing the tasks successfully.

One such mediating dynamic is evident when examining cognitive dissonance post-adoption confirmation. Because users come to a platform with significant fear and technical difficulty, very often due to strictly enforced security features and social pressures, they expect a minimum level of functionality. Over time, their early anxiety dissipates into an improved appreciation of how well the platform works when they avoid error-prone system interfaces. If, however, these first-stage technical difficulties can be overcome, that will improve user satisfaction and generate a stronger sense of achievement, as in an environment with little friction. Increased satisfaction is a former key motivator that has strengthened and stabilized the behavioral intention to permanently integrate the platform into everyday business processes. This mediation framework is then statistically validated to show that technology anxiety does not just block adoption but can also lead to a positive attitude towards user attention and commitment, provided the right structural safeguards are in place to support long-term user satisfaction and the upkeep of these systems. In terms of explanatory power, the structural model accounted for $R^2 = 0.480$ (adjusted $R^2 = 0.475$) of the variances in Technology Anxiety, $R^2 = 0.599$ (adjusted $R^2 = 0.597$) of the variance in User Satisfaction, and $R^2 = 0.151$ (adjusted $R^2 = 0.143$) of the variance in Behavioral Intention. Effect sizes (f^2) were as follows: Perceived Safety → Tech-Anxiety, $f^2 = 0.331$ (medium-to-large); Social Influence → Tech-Anxiety, $f^2 = 0.064$ (small); Tech-Anxiety → Satisfaction, $f^2 = 1.492$ (very large); Tech-Anxiety → Behavioral Intention (direct), $f^2 = 0.013$ (negligible, consistent with its non-significance); Satisfaction → Behavioral Intention, $f^2 = 0.120$ (small-to-medium). Predictive relevance (Q^2, cross-validated redundancy via 10-fold blindfolding) was positive for both endogenous outcomes with a mediating role: $Q^2 = 0.164$ for User Satisfaction and $Q^2 = 0.009$ for Behavioral Intention, indicating the model has predictive relevance for both, though this relevance is weak for Behavioral Intention given its low R^2. Collinearity

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was assessed at two levels. Inner-model VIF values were low (PS and SI as predictors of ANX: VIF = 1.61; ANX and SAT as predictors of BI: VIF = 2.49), well below the conservative threshold of 3.0, ruling out multicollinearity as a concern for the path estimates. A full-collinearity test (Kock, 2015) was also conducted as a common-method-bias check, regressing each construct on all others in the model; all resulting VIFs ranged from 1.05 to 3.03, below the 3.3 threshold conventionally used to flag common method bias, though the values involving Technology Anxiety and Satisfaction (VIF ≈ 3.0) were the closest to this threshold and should be interpreted with some caution.

Table 8. Vertical Profile of Structural Mediation Validation for Hypothesis 3

Parameter / Statistical Metric	Empirical Value and Analytical Details
Hypothesis Reference	H3 (Mediation Path)
Structural Relationship	Tech-Anxiety (ANX) → User Satisfaction (SAT) → Behavioral Intention (BI)
Specific Indirect Effect (βindirect)	0.389
Standard Error (SE)	0.082
t-statistic	4.73
p-value	<0.001
95% Bias-Corrected Confidence Interval	[0.228, 0.551] (Excludes zero, confirming statistical significance)
Empirical Decision	Supported — Indirect-only (Full) Mediation. Direct effect ANX→BI: β = -0.167, t = 1.63, p = 0.104 (not significant, 95% CI [-0.355, 0.064]). Total effect ANX→BI: β = 0.222, t = 2.67, p < 0.01 (significant). Per Zhao et al. (2010), a significant indirect effect combined with a non-significant direct effect indicates indirect-only (full) mediation, not complementary mediation.

3.3. Theoretical Implications

This study contributes to technology adoption theory by suggesting that, within a challenge–hindrance stressor framing, Technology Anxiety need not be treated only as a

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hindrance construct that uniformly suppresses satisfaction and adoption. The positive associations observed between Perceived Safety and Technology Anxiety, and between Technology Anxiety and User Satisfaction, are consistent with a possible productive-vigilance interpretation, in which structural safeguards and social accountability are associated with heightened attentiveness rather than avoidance. However, because cognitive vigilance, mastery, and productive friction were not directly measured as independent constructs in this study, this interpretation should be treated as a theoretical proposition for future validation rather than a confirmed psychological mechanism. This distinction refines classical TAM/UTAUT assumptions, which generally treat anxiety as a uniformly negative antecedent, by highlighting that its relationship with downstream outcomes may depend on context-specific factors such as institutional stakes and social accountability.

3.4. Practical Implications

For platform developers and school administrators, these findings suggest that the presence of technology anxiety among teachers should not automatically be treated as a sign that a blended learning platform needs fewer safeguards or less institutional oversight. At the same time, because excessive anxiety could plausibly become harmful rather than productive, institutions should not deliberately amplify anxiety as an adoption strategy. Instead, practical efforts should focus on transparent communication about why security procedures exist, adequate training on the platform's safety features, and accessible technical support and help resources, so that teachers' attentiveness is channeled constructively rather than left unsupported.

3.5. Limitations and Future Research

Despite its insights, this study possesses distinct limitations. First, discriminant validity between Perceived Safety and Technology Anxiety could not be fully established. Although the Fornell-Larcker criterion supported discriminant validity for this pair, the more sensitive HTMT criterion did not: the point estimate (HTMT = 0.891) exceeded the conservative 0.85 threshold, and its bootstrap confidence interval [0.729, 1.061] included 1, meaning the two constructs cannot be shown to be statistically distinct in this sample. This is plausibly explained by the theoretical closeness of the two constructs within the Transactional Theory of Stress and Coping used in this study: the appraisal of a platform

as safe or unsafe (Perceived Safety) sits conceptually just upstream of the affective response to that appraisal (Technology Anxiety), and with only two items measuring each construct, there was limited room to empirically separate them. This is reported transparently rather than resolved, and future studies should measure Perceived Safety and Technology Anxiety with more items each, ideally four or more, to allow a clearer empirical test of their distinctiveness. Second, the data is cross-sectional, capturing a specific snapshot of teachers' psychological states during a blended learning transition. Future research should utilize longitudinal designs to observe the exact inflection point where constructive vigilance (eustress) degenerates into harmful exhaustion (distress).
Third, the sample is restricted to high school teachers in North Sumatra, Indonesia, operating under centralized administrative pressures. Future studies should replicate this model across different cultural contexts and organizational structures—such as corporate or healthcare settings—to test the generalizability of the positive anxiety-satisfaction pathway. Finally, integrating objective usage logs alongside subjective self-reports could provide a more granular understanding of how cognitive vigilance manifests in actual system interactions.

4. CONCLUSION

This research has examined the relationships among perceived safety, social influence, technology anxiety, satisfaction, and behavioral intention in a blended learning setting, considering whether contextual vigilance and social influence may be associated with user intention [32]. This study presents a more fine-grained perspective designed to hone classical technology acceptance models by assessing a holistic structural model across an entire dataset (N = 205 respondents). The empirical results confirm that both Perceived Safety (β = 0.526, t = 8.171) and Social Influence (β = 0.232, t = 3.60) are positively associated with Tech-Anxiety, jointly explaining 48.0% of the variance in Tech-Anxiety (R^2 = 0.480). Rather than functioning simply as a barrier that prevents user engagement, technology anxiety in this sample was positively associated with satisfaction, which is consistent with a possible productive-vigilance interpretation. When a platform has strong safety guarantees and is backed by significant organizational or peer commitments to follow through with procedures, teachers may come to see operational stakes and procedural requirements as salient. This interpretation, however, remains

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speculative and requires direct measurement of vigilance in future research. Furthermore, the significant mediation pattern is further reflected in the indirect effect of Technology Anxiety on Behavioral Intention through User Satisfaction ($\beta_{indirect}$=0.389, t=4.73, p<0.001). It is common for users to feel skeptical or uncomfortable when a new system is introduced, and technical friction can plausibly contribute to non-adoption in some cases. In this sample, however, Technology Anxiety was positively, not negatively, associated with post-adoption User Satisfaction (R^2 = 0.599), and User Satisfaction was in turn the strongest correlate of Behavioral Intention (R^2 = 0.151).

These findings suggest that platform developers and school administrators should not necessarily treat all forms of technology anxiety as something to be eliminated, but rather should distinguish potentially harmful anxiety from productive vigilance, and support teachers through transparent security explanations, adequate training, and accessible help resources rather than relying on anxiety itself as an adoption strategy. As this study relies on cross-sectional, self-reported data from a single regional sample, these conclusions should be treated as associations rather than confirmed causal or long-term outcomes. Future research should employ longitudinal designs, objective usage data, and multiple platform contexts to test whether the productive-vigilance interpretation holds over time.

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