



RECEIVED 16 March 2026
ACCEPTED 7 July 2026
PUBLISHED 31 October 2026

CITATION
Awaluddin M, Nurcahyanto H,
(2026). Strategic Digital Learning
Platform Utilization: the Roles of
User Experience, Trust, and Task-
Technology Fit. Ilomata
International Journal of
Management. 7 (4), 1317-1326.
doi: 10.61194/ijim.v7i4.2308

TYPE Original Research
PUBLISHED 31 October 2026
DOI 10.61194/ijim.v7i4.2308
VOL 7 Issue 4 October 2026

COPYRIGHT
© 2026 Awaluddin and
Nurcahyanto. This is an open-
access article distributed under
the terms of the Creative
Commons Attribution License (CC
BY). The use, distribution or
reproduction in other forums is
permitted, provided the original
author(s) and the copyright
owner(s) are credited and that the
original publication in this journal
is cited, in accordance with
accepted academic practice. No
use, distribution or reproduction
is permitted which
does not comply with these
terms.

Strategic Digital Learning Platform Utilization: the Roles of User Experience, Trust, and Task-Technology Fit

Muhammad Awaluddin¹, Himawan Nurcahyanto²

^{1,2}Univeristas Telkom, West Java, Indonesia

Correspondence: awaluddin@telkomuniversity.ac.id¹

Abstract

The rapid development of digital technologies has transformed how individuals utilize digital learning platforms for knowledge sharing, collaboration, and professional development. Previous studies have primarily examined technology adoption factors separately, while limited research has integrated user experience, trust, and task-technology fit within a single framework to explain behavioral intention and actual use behavior. Therefore, this study aims to analyze the effects of user experience, trust, task characteristics, and technology characteristics on task-technology fit, behavioral intention, and use behavior in digital learning platforms. A quantitative approach was employed using survey data collected from 200 active users of digital learning platforms involved in educational and professional learning activities. Data were analyzed using descriptive statistics and multiple regression analysis. The results indicate that task characteristics ($\beta = 0.31, p < 0.001$) and technology characteristics ($\beta = 0.37, p < 0.001$) significantly influence task-technology fit ($R^2 = 0.44$). User experience ($\beta = 0.34, p < 0.001$), trust ($\beta = 0.29, p < 0.001$), and task-technology fit ($\beta = 0.28, p < 0.001$) significantly affect behavioral intention, explaining 48% of the variance ($R^2 = 0.48$). Behavioral intention also significantly influences use behavior ($\beta = 0.41, p < 0.001$), with $R^2 = 0.36$. These findings demonstrate that positive user experience, trust, and alignment between platform capabilities and user tasks contribute to stronger behavioral intention and actual platform usage. This study contributes to the literature by proposing an integrated user-level model that combines user experience, trust, and task-technology fit to explain digital learning platform utilization.

KEYWORDS

digital learning platforms; user experience; trust; task-technology fit; behavioral intention; use behavior.

Introduction

Digital learning platforms have become an important medium for supporting knowledge sharing, collaboration, and professional development activities. The rapid development of internet technologies and mobile devices has enabled educational institutions and organizations to provide flexible and scalable learning environments. The increasing adoption of digital learning technologies has accelerated the integration of online learning platforms into educational and professional contexts, making platform utilization an important issue for both researchers and practitioners.

Previous studies have identified behavioral intention as one of the most important predictors of technology usage behavior. In addition, trust and user experience have been recognized as important factors influencing users' willingness to adopt digital technologies. The Task-Technology Fit (TTF) perspective further suggests that technology is more likely to be utilized when its capabilities effectively support users' tasks. Although these factors have been widely examined individually, limited studies have integrated user experience, trust, and task-technology fit into a single framework to explain behavioral intention and actual use behavior in digital learning platforms.

Therefore, this study aims to examine the effects of user experience, trust, task characteristics, and technology characteristics on task-technology fit, behavioral intention, and use behavior.

The rapid growth of digital learning platforms has attracted increasing attention from researchers investigating factors influencing user adoption and technology acceptance. Behavioral intention has been widely recognized as one of the most important predictors of technology usage behavior. Users are more likely to adopt digital platforms when they perceive that the technology provides clear benefits and supports their learning activities effectively (Alyoussef, 2021).

Trust has also been identified as a critical determinant influencing digital platform adoption. Trust reflects users' perceptions regarding system reliability, security, and credibility. Users who perceive digital platforms as trustworthy tend to demonstrate stronger behavioral intentions to use digital services for learning activities (Nagy & Hajdu, 2022).

User experience represents another important factor influencing the adoption of digital platforms. User experience describes the overall interaction between users and the system, including interface usability, system accessibility, and service quality. Positive user experience can increase user satisfaction and strengthen engagement with digital learning platforms (Ifenthaler, 2022).

Technology adoption in digital learning environments is also influenced by the alignment between technological capabilities and users' learning tasks. The Task-Technology Fit theory explains that technology will be utilized more effectively when its functionalities support the requirements of user tasks. When the technology adequately supports learning activities, users tend to perceive the platform as more useful and are more likely to adopt it (Al-Fraihat et al., 2020).

Digital learning platforms operate within a broader digital learning platforms that integrates users, digital infrastructure, and knowledge resources. In this study, however, this digital learning platforms is positioned strictly as the contextual environment supporting platform utilization, rather than as an empirical unit of analysis involving strategic macro-governance, complementors, interoperability, or inter-organizational network effects. The sustainability and success of these systems depend heavily on individual-level behavioral factors and immediate user acceptance. Therefore, instead of evaluating broad ecosystem-level mechanisms, the empirical model of this study focuses explicitly on user-level behavioral determinants—specifically analyzing how individual user experience, trust, and task compatibility interact to drive actual platform adoption within this digital environment

Task characteristics and technology characteristics play an important role in shaping the level of task-technology fit within digital learning systems. Task characteristics represent the nature of activities performed during the learning process, while technology characteristics refer to the functional capabilities provided by the digital platform. A higher level of compatibility between these elements can increase users' perceived usefulness and behavioral intention toward platform adoption

Digital learning platforms provide technology-enabled environments that facilitate learning activities, communication, and access to educational resources. Understanding the factors that influence users' behavioral intention and actual use behavior is therefore important for improving platform effectiveness and encouraging continued utilization.

Digital Learning Platforms

Digital learning platforms have become an essential infrastructure supporting knowledge exchange, professional

development, and online education delivery. Digital learning platforms facilitate learning accessibility, collaboration, and user engagement in educational and professional contexts. Digital platforms increasingly support knowledge sharing and collaborative learning processes by integrating multiple technological tools within a unified online environment (Jang et al., 2024). These platforms provide integrated systems that combine learning content, communication tools, and digital interaction features that enable learners to access educational resources efficiently. According to Zawacki-Richter et al. (2019), digital learning technologies have evolved from simple content management systems into complex digital learning platforms that support collaborative learning, adaptive technologies, and interactive educational experiences.

The development of digital platforms has also transformed the structure of education and professional training environments. Online learning technologies enable organizations and institutions to deliver scalable training programs while improving accessibility for learners in different geographical locations. Research conducted by Hodges et al. (2020) explains that digital platforms have become an important mechanism for sustaining learning activities, particularly as institutions increasingly adopt technology-mediated learning environments.

Digital learning platforms function as technology-mediated learning environments by integrating communication tools, structured learning content, and interactive digital features within a unified interface. Prior studies indicate that user experience, trust, and task-technology compatibility are critical determinants influencing individual behavioral intention and sustained platform utilization. Although digital learning platforms are widely adopted across educational settings, this study specifically focuses on individual users' perceptions and behaviors when interacting with these platforms. By narrowing the scope to individual behavior, the empirical analysis isolates how specific user perceptions and task-technology configurations directly determine actual platform adoption.

Trust in Digital Platforms

Trust represents an important determinant influencing the adoption of digital technologies. A meta-analysis of digital platform studies shows that trust is one of the strongest predictors influencing users' intention to engage with online platforms (Oesterreich et al., 2024). In digital environments, users rely on online systems to access information, communicate with others, and manage personal data. Trust therefore reflects users' confidence in the reliability and security of digital systems. Research conducted by McKnight et al. (2020) indicates that trust significantly influences individuals' willingness to engage with digital services and participate in online interactions.

Digital learning platforms require users to interact with online content and digital infrastructures that process personal information and learning data. Rahi et al. (2021) explain that trust reduces users' perceived risks when interacting with digital platforms. Higher levels of trust can therefore increase users' confidence in using digital technologies for learning purposes. Studies on digital commerce platforms also demonstrate that trust significantly strengthens users' willingness to adopt and continuously use online services

The role of trust becomes increasingly important in platform-based environments where digital services are delivered through complex technological infrastructures. Gefen et al. (2022) argue that trust contributes to the development of long-term relationships between users and digital platforms. Users who perceive digital systems as reliable and secure tend to demonstrate stronger engagement with digital services.

User Experience

User experience refers to the perceptions and responses

that arise from users' interactions with digital systems. User experience differs from perceived ease of use, usability, satisfaction, and service quality because it reflects users' holistic cognitive and emotional responses during interaction with a digital platform. Perceived ease of use mainly emphasizes the degree to which a system is considered easy to operate, while usability focuses on interface efficiency and functionality. Satisfaction generally represents users' post-usage evaluation, whereas service quality emphasizes the quality of services delivered by the platform. In contrast, user experience encompasses broader interaction dimensions including interface perception, interaction quality, accessibility, emotional engagement, and overall user perception during system utilization. It includes several important aspects such as usability, accessibility, interface design, interaction quality, and overall satisfaction during system use. Therefore, the indicators used in this study, including interface usability, navigation efficiency, and interaction quality, are conceptualized as dimensions representing the broader user experience construct rather than as isolated measures of usability or satisfaction alone. In digital platforms, user experience becomes an important factor because it determines how easily users can interact with a system and complete their tasks effectively. Systems that provide intuitive interfaces and efficient navigation structures tend to generate more positive perceptions from users and increase their willingness to continue using digital technologies.

Positive user experience can significantly influence user satisfaction and technology adoption behavior. When users experience smooth interactions, responsive system performance, and well-organized interface layouts, they tend to perceive the system as more useful and reliable. Research conducted by [Febriyanto et al. \(2025\)](#) shows that user experience has a significant effect on users' intentions to continue using digital platforms, particularly in online marketplace environments where system interaction quality directly affects user engagement and retention ([Febriyanto et al., 2025](#)).

In digital learning environments, user experience plays a crucial role in determining how learners interact with educational content and digital interfaces. Learning platforms that provide clear navigation structures, responsive features, and visually organized content can facilitate more effective learning interactions. Conversely, poorly designed interfaces or complicated navigation systems may reduce learner engagement and create difficulties in accessing learning materials. Studies on usability in learning technologies emphasize that user-centered design is essential to ensure that digital learning systems support users' cognitive processes and learning activities effectively ([Lu et al., 2025](#)).

Interface transparency and system usability are also important components of user experience. When digital platforms provide simple and intuitive interaction mechanisms, users are more likely to trust the system and feel comfortable using it repeatedly. The application of user-centered design principles in interface development can significantly improve usability and overall user satisfaction because system features are designed based on users' needs and expectations.

User experience also contributes to how users evaluate the effectiveness of digital platforms in supporting their activities. In educational contexts, responsive interfaces and efficient system navigation enable learners to focus more on learning tasks rather than technical difficulties. Research on digital learning systems indicates that positive user experience can increase engagement, satisfaction, and perceived learning effectiveness because users can interact with the system more comfortably and efficiently ([El Aadmi-Laamech et al., 2024](#)).

Therefore, improving user experience has become an essential strategy in digital platform development. Platforms that prioritize usability, accessibility, and intuitive interface design are more likely to enhance user satisfaction, strengthen engagement, and encourage continuous system usage in both educational and technological environments.

Task–Technology Fit

The Task–Technology Fit (TTF) theory explains the relationship between technological capabilities and the tasks performed by users. The theory suggests that technology will produce better outcomes when its features align with the requirements of users' activities. When a technological system provides functionalities that directly support users' tasks, individuals are more likely to utilize the system effectively and achieve improved performance outcomes. The concept of task–technology fit was originally introduced to explain how the alignment between task requirements and technological capabilities influences system utilization and user performance ([Goodhue & Thompson, 1995](#)).

Task–technology fit emphasizes that technology adoption does not depend solely on the availability of technological tools, but also on how well those tools support the tasks that users need to perform. When technology provides appropriate features that facilitate task completion, users tend to perceive the system as more useful and effective. Conversely, when technological systems fail to support task requirements, users may experience difficulties that reduce their motivation to use the system. Recent studies continue to confirm that the alignment between task needs and technological features significantly influences user perceptions and system utilization in digital environments ([Al-Emran et al., 2022](#)).

In modern digital learning environments, the relevance of task–technology fit has become increasingly important because online learning platforms are expected to support various academic activities such as accessing learning materials, participating in discussions, submitting assignments, and interacting with instructors. Research indicates that users are more likely to adopt digital learning technologies when the system provides functionalities that directly support these learning activities. [Isaac et al. \(2019\)](#) explain that individuals tend to adopt technologies that provide relevant capabilities for completing their tasks efficiently, particularly when those technologies simplify complex learning processes.

Task characteristics represent the nature of activities performed during learning processes, such as searching for information, collaborating with peers, and completing academic assignments. Meanwhile, technology characteristics refer to the capabilities, functions, and features provided by digital learning platforms. These may include system accessibility, content management features, communication tools, and user interface design. [Lin & Wang \(2021\)](#) explain that the compatibility between task characteristics and technology characteristics determines the level of task–technology fit within digital learning systems. When digital platforms offer features that effectively support learning activities, users tend to perceive the system as more useful and beneficial for their academic performance. Task characteristics determine the nature and complexity of learning activities performed by users. When digital learning platforms are capable of supporting these task requirements effectively, users are more likely to perceive a stronger level of task–technology fit. Similarly, technology characteristics such as system functionality, accessibility, and platform flexibility contribute to the ability of the system to accommodate users' learning activities. Therefore, both task characteristics and technology characteristics are expected to positively influence task–technology fit within digital learning environments.

Empirical research also demonstrates that task–

technology fit plays an important role in shaping users' perceptions toward digital learning platforms. Wu & Chen (2021) found that when users perceive that digital technologies adequately support their learning tasks, they are more likely to develop positive attitudes toward the system and demonstrate stronger intentions to continue using the platform. Similarly, Al-Emran et al. (2022) emphasize that high levels of task-technology fit can improve perceived usefulness, enhance user satisfaction, and strengthen behavioral intention toward adopting digital learning technologies. When users perceive that digital platforms effectively support their learning activities and task requirements, they are more likely to develop positive behavioral intentions toward continued platform utilization. Higher levels of task-technology fit increase users' perceptions that the platform is beneficial, relevant, and capable of improving learning effectiveness, which subsequently strengthens behavioral intention.

Therefore, achieving a strong alignment between task requirements and technological capabilities is essential for ensuring the effectiveness of digital learning platforms. When digital systems are designed to support the specific needs of users' activities, they can improve learning efficiency, increase user engagement, and encourage sustained technology adoption in educational environments.

To provide a rigorous framework for empirical testing, the proposed model evaluates how relational, experiential, and structural alignment factors concurrently drive user behavior. First, trust and user experience serve as critical precursors to behavioral intention; trust reduces perceived risk and increases user confidence in platform safety (McKnight et al., 2020), while a seamless user experience satisfies cognitive and emotional demands during system interaction. Second, according to Task-Technology Fit (TTF) theory, fit is a multi-dimensional construct determined by both the nature of the work and the capabilities of the tool (Goodhue & Thompson, 1995). Task characteristics (the complexity and demands of learning activities) and technology characteristics (system features and functionality) serve as the essential inputs that interact to produce a high level of task-technology compatibility. Third, when individual users perceive a strong fit between platform features and their specific learning tasks, they recognize the system's functional utility, which directly enhances their behavioral intention to utilize the platform (Al-Emran et al., 2022). Finally, action-reasoning models consistently dictate that cognitive commitment and readiness serve as the immediate precursor to actual behavior; therefore, a strong behavioral intention directly translates into a higher frequency and depth of actual platform utilization (Wibowo et al., 2024). Based on these theoretical relationships, the following hypotheses are proposed:

H1: Trust positively influences behavioral intention.

H2: User experience positively influences behavioral intention.

H3: Task characteristics positively influence task-technology fit.

H4: Technology characteristics positively influence task-technology fit.

H5: Task-technology fit positively influences behavioral intention.

H6: Behavioral intention positively influences use behavior.

Behavioral Intention and Use Behavior

Behavioral intention refers to an individual's willingness and readiness to adopt and use a particular technology. In the context of digital systems, behavioral intention is considered one of the most important determinants of whether individuals will actually utilize technological platforms. Technology adoption studies consistently identify behavioral intention as a key construct that reflects users' motivation

and planned future use of a system. Individuals who possess stronger behavioral intentions tend to demonstrate higher levels of commitment to adopting and integrating technology into their daily activities and professional tasks (Wibowo et al., 2024).

Behavioral intention is generally formed through users' cognitive evaluations of a technology, particularly regarding its perceived usefulness and ease of use. When individuals believe that a digital system can improve their performance, efficiency, or productivity, they are more likely to develop a stronger intention to use the technology. Research conducted by Wibowo et al. (2024) shows that positive perceptions toward digital platforms significantly increase users' intention to adopt and continue using technological systems. Similarly, Duan et al. (2026) explain that individuals who perceive digital technologies as beneficial and easy to operate tend to demonstrate stronger behavioral intentions toward technology adoption.

In addition to perceived usefulness and usability, psychological and contextual factors also influence behavioral intention. Trust plays a significant role in shaping users' willingness to adopt digital systems, particularly in online environments where security and reliability are major concerns. Budiyo et al. (2025) state that users who perceive digital systems as trustworthy and reliable are more likely to develop stronger intentions to adopt such technologies. Trust and perceived risk significantly influence individuals' intentions to use digital services, especially in financial technology platforms.

Furthermore, technological environments and user capabilities can also strengthen behavioral intention. Factors such as digital literacy, technological infrastructure, and system innovation contribute to how individuals evaluate digital technologies. According to Schrank (2025), technological innovation and system intelligence can positively influence users' behavioral intention by increasing perceptions of usefulness, efficiency, and service quality. When individuals perceive that a digital system offers advanced features and reliable performance, their intention to adopt and use the technology tends to increase.

Use behavior represents the actual interaction between users and digital systems once behavioral intention has been formed. It reflects how individuals incorporate technology into their daily activities, organizational tasks, or learning environments. Individuals with strong behavioral intention are more likely to access digital platforms more frequently and integrate them into their routines. Wibowo et al. (2024) emphasize that behavioral intention is a significant predictor of actual technology usage, indicating that stronger intention levels typically lead to higher levels of system utilization.

Empirical research also confirms that positive user perceptions toward digital technologies contribute to sustained technology usage over time. Budiyo et al. (2025) demonstrate that users who perceive digital platforms as useful, secure, and beneficial tend to maintain continuous usage behavior. Therefore, understanding the relationship between behavioral intention and use behavior is essential for researchers and organizations aiming to improve the adoption and long-term utilization of digital technologies.

Despite extensive research on technology adoption, there remains a critical gap in literature regarding the simultaneous interaction between experiential (user experience), relational (trust), and structural (task-technology alignment) factors within a single framework. Most prior studies utilize the Technology Acceptance Model (TAM) or Task-Technology Fit (TTF) in isolation, frequently neglecting how emotional user experience and trust parameters interact with structural task alignment. Therefore, the theoretical novelty of this study lies in proposing and validating an integrated individual-level adoption model that combines user experience, trust, and TTF

to explain digital learning platform utilization. By clarifying these individual-level behavioral mechanics within a digital learning context, this study offers a more holistic framework that goes beyond conventional technology adoption models, providing specific insights for platform developers to maximize user engagement through targeted system alignment.

Methods

Research Design

This study adopts a quantitative research approach to examine the factors influencing individual users' adoption and utilization of digital learning platforms. The quantitative approach enables systematic measurement of user perceptions and statistical testing of the proposed relationships among trust, user experience, task–technology fit, behavioral intention, and use behavior. Quantitative research enables systematic measurement of user perceptions and statistical testing of theoretical relationships among the proposed variables.

The study applies a cross-sectional survey design in which data are collected from respondents at a single point in time. Cross-sectional surveys allow researchers to capture perceptions and behavioral responses of technology users efficiently. This approach is commonly used in studies examining digital platform usage and technology adoption in organizational and educational environments.

The proposed research model examines the influence of trust, user experience, task characteristics, and technology characteristics on task–technology fit and behavioral intention, which subsequently affect use behavior in digital learning platforms.

Population and Sample

The population of this study consists of individuals who actively use digital learning platforms for education, training, or professional development activities. The expansion of digital learning technologies has significantly increased the number of users participating in online learning environments across various professional sectors (Bond et al., 2021).

A purposive sampling technique is applied to select respondents who meet specific criteria relevant to the research objectives. Respondents were recruited through online learning communities, university learning groups, and professional training networks using online survey distribution channels. Respondents must have experience using digital learning platforms within the last six months and be familiar with digital learning systems such as online courses, training platforms, or learning management systems. Screening questions were included at the beginning of the questionnaire to ensure that only respondents with recent experience using digital learning platforms were eligible to participate in the study. Purposive sampling allows researchers to select participants who possess the relevant knowledge and experience necessary to evaluate digital platform usage (Etikan & Bala, 2021).

The sample size of 200 respondents was considered adequate for multiple regression analysis. Following the recommendation of Hair et al. (2022), regression analysis requires an adequate ratio between the number of observations and predictors to achieve sufficient statistical power and stable coefficient estimation. Since the study model contains a limited number of predictors, the sample size exceeded the minimum recommended threshold and was therefore considered appropriate for hypothesis testing. In addition, the sample size satisfies the general recommendation for behavioral research, which suggests a minimum sample exceeding 150 observations for regression models involving multiple independent variables.

Data Collection Method

Prior to the main survey distribution, a pilot test involving 30 respondents was conducted to evaluate the clarity, readability, and consistency of the questionnaire items. The pilot test results indicated that all items were understandable and demonstrated acceptable reliability levels. Data were collected using a structured questionnaire distributed through an online survey. Online surveys allow efficient data collection and enable researchers to reach respondents who actively interact with digital platforms. The use of online questionnaires has become increasingly common in digital technology research due to its accessibility and flexibility in collecting large datasets.

The questionnaire consists of several sections designed to measure the constructs included in the research model (see Table 1). Respondents were asked to evaluate a series of statements related to their experiences when interacting with digital learning platforms.

Participation in this study was voluntary, and respondents were informed that their responses would remain anonymous and confidential. All participants provided informed consent before completing the questionnaire.

All questionnaire items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The Likert scale was selected because it is widely used in behavioral and technology adoption research to measure users' perceptions and attitudes toward digital systems.

Each construct is measured using several indicators adapted from previously validated measurement scales in digital technology adoption studies.

The measurement items were adapted from previously validated studies in digital technology and information systems research. Trust was measured using four items adapted from Gefen et al. (2022), while user experience was measured using four items adapted from Febriyanto et al. (2025). Task characteristics and technology characteristics were each measured using three items adapted from Goodhue & Thompson (1995) and Isaac et al. (2019). Task–technology fit was measured using four items adapted from Lin & Wang (2021). Behavioral intention and use behavior were measured using three items each adapted from Wibowo et al. (2024). Minor wording modifications were applied to ensure compatibility with the digital learning platform context.

Data Analysis Technique

Data analysis was conducted using several statistical procedures to evaluate the proposed research model. The analysis began with descriptive statistical analysis to examine respondent characteristics and summarize response distributions. Descriptive statistics provide an overview of the dataset and help identify general patterns in users' perceptions of digital learning platforms (Field, 2022). Next, reliability testing was performed using Cronbach's Alpha to assess the internal consistency of measurement.

Table 1. Measurement of Variables

Variable	Indicators
Trust	platform reliability, credibility of information, data security
User Experience	interface usability, navigation efficiency, interaction quality
Task Characteristics	complexity of learning tasks, learning activity frequency
Technology Characteristics	system functionality, platform features, content accessibility
Task–Technology Fit	compatibility between platform capabilities and learning activities
Behavioral Intention	willingness to continue using digital learning platforms
Use Behavior	frequency of platform usage and engagement with learning content

items. A Cronbach's Alpha value greater than 0.70 indicates acceptable reliability for research instruments (Hair et al., 2022).

Validity testing was conducted through correlation analysis and factor loading evaluation to ensure that each indicator accurately measures its intended construct. Indicators demonstrating strong correlations with their respective constructs are considered valid.

To test the proposed hypotheses, multiple regression analysis was employed to examine the relationships among variables in the research model. Regression analysis enables researchers to analyze the influence of several independent variables on dependent variables simultaneously and determine the significance of each relationship (Hair et al., 2022).

To evaluate the proposed hypotheses and ensure structural internal consistency, data analysis was executed via ordinary least squares (OLS) multiple linear regression using a series of separate, sequential regression equations to examine the multi-stage path model. Prior to hypothesis testing, rigorous diagnostic evaluations were conducted to verify that the dataset adhered to all standard statistical assumptions for linear regressions.

Normality was evaluated using both the Kolmogorov-Smirnov and Shapiro-Wilk tests for each regression equation. All dependent variables produced non-significant results ($p > 0.05$), indicating that the assumption of normality was satisfied.

Multicollinearity was assessed using Tolerance and Variance Inflation Factor (VIF). All tolerance values exceeded 0.10, while VIF values ranged from 1.24 to 1.86, indicating no multicollinearity.

Heteroscedasticity was examined using the Glejser test for each regression equation. All predictor variables produced non-significant coefficients ($p > 0.05$), indicating that heteroscedasticity was not detected.

All statistical analyses were performed using IBM SPSS Statistics Version 26.

The regression model examines the following relationships:

The proposed sequential regression framework examines the six hypothesized relationships through three interconnected structural equations to ensure methodological coherence and internal consistency.

Task-Technology Fit Model

Task Characteristics → Task-Technology Fit

Technology Characteristics → Task-Technology Fit

Behavioral Intention Model

Trust → Behavioral Intention

User Experience → Behavioral Intention

Task-Technology Fit → Behavioral Intention

Use Behavior Model

Behavioral Intention → Use Behavior

This hierarchical modeling approach reflects the theoretical sequence in which task and technology factors influence task-technology fit, which subsequently affects users' behavioral intentions alongside trust and user experience, ultimately leading to actual use behavior.

Result and Discussion

Respondent Profile

A total of 200 respondents participated in this study. Respondents consisted of individuals who actively use digital learning platforms for educational and professional development purposes. The demographic characteristics of respondents provide an overview of the user profile involved in the study.

Table 2 presents the demographic distribution of

respondents based on gender, age group, and usage experience.

The results indicate that most respondents fall within the 18–35 age range, which represents active users of digital learning platforms. Nearly 46% of respondents have used digital learning platforms for 1–3 years, indicating moderate experience with digital learning technologies

Descriptive Statistics

Descriptive statistics were calculated to examine the distribution of responses for each construct in the research model (see Table 3).

The descriptive statistics show that the average scores for all variables are above 3.5, indicating generally positive perceptions of digital learning platforms among respondents. The highest mean value is observed for behavioral intention (3.95), suggesting a strong willingness among users to continue using digital learning platforms. Common method bias was assessed using Harman's single-factor test. The results showed that the first factor accounted for less than 50% of the total variance, indicating that common method bias was not a significant concern in this study.

Reliability Analysis

Reliability testing was conducted using Cronbach's Alpha to evaluate the internal consistency of measurement items (see Table 4).

All constructs demonstrate Cronbach's Alpha values above 0.70, indicating that the measurement items have acceptable reliability for further analysis (Hair et al., 2022).

The histogram illustrates the distribution pattern of the behavioral intention variable among respondents (see Figure 1)

Table 2. Respondent Demographic Characteristics

Category	Frequency	Percentage
Male	112	56%
Female	88	44%
Age		
18–25 years	94	47%
26–35 years	72	36%
36–45 years	24	12%
>45 years	10	5%
Experience Using Digital Learning Platforms		
<1 year	38	19%
1–3 years	92	46%
>3 years	70	35%

Table 3. Descriptive Statistics

Variable	Mean	Standard Deviation
Trust	3.86	0.71
User Experience	3.92	0.66
Task Characteristics	3.74	0.72
Technology Characteristics	3.88	0.69
Task-Technology Fit	3.81	0.68
Behavioral Intention	3.95	0.64
Use Behavior	3.84	0.70

Table 4. Reliability Test Results

Variable	Cronbach's Alpha
Trust	0.84
User Experience	0.86
Task Characteristics	0.81
Technology Characteristics	0.83
Task-Technology Fit	0.88
Behavioral Intention	0.87
Use Behavior	0.82

The shape of the histogram shows a relatively symmetric pattern with most observations concentrated around the mean value.

Such distribution patterns often indicate that the dataset approximates a normal distribution, which is a common assumption in parametric statistical analysis.

Research in quantitative data analysis emphasizes that normally distributed variables tend to produce more reliable statistical estimation in regression models (Kline, 2023). In the figure, the normal curve overlay aligns closely with the frequency bars, indicating that the behavioral intention scores follow an approximately normal distribution.

Most respondents demonstrate moderate to high levels of intention to continue using digital learning platforms. Patterns like this commonly appear in digital technology adoption studies where users already possess prior experience with

online systems (Dwivedi et al., 2023).

Validity Analysis

Construct validity was assessed through correlation analysis between indicators and their respective constructs. The results indicate that all indicators show factor loading values above 0.60, suggesting adequate convergent validity.

The results indicate that all measurement items meet the recommended validity threshold (see Table 5).

Hypothesis Testing

Correlation analysis was conducted to examine the relationships among the variables before performing regression analysis (see Table 6).

The regression results indicate that all proposed

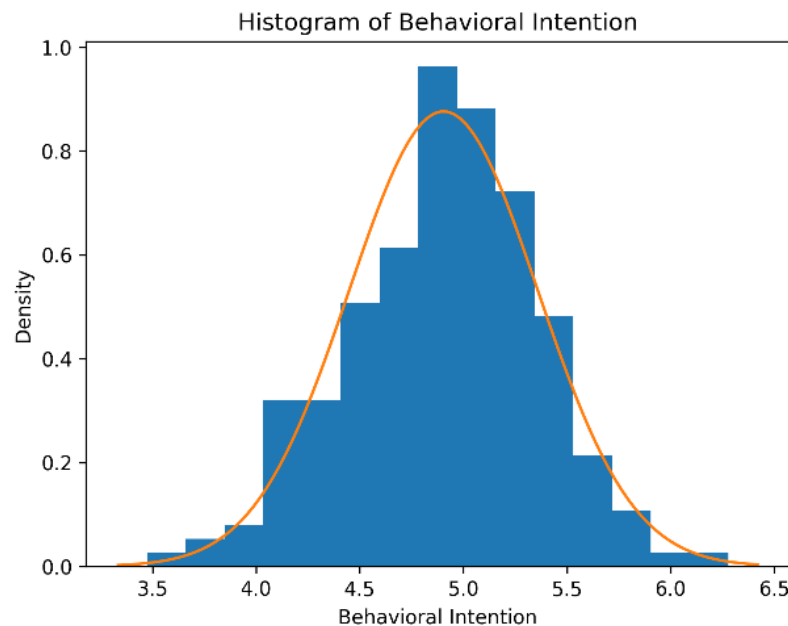


Figure 1. Histogram of Behavioral Intention

Table 5. Validity Test (Item-Level Factor Loadings via Principal Component Analysis)

Variable	Item Code	Indicator Measurement Item	Factor Loading	Status
Trust	TR1	Platform reliability and system uptime	0.84	Valid
	TR2	Credibility and accuracy of hosted information	0.79	Valid
	TR3	Data security and privacy protection measures	0.75	Valid
	TR4	System integrity and safety safeguards	0.72	Valid
User Experience	UX1	Interface usability and ease of interaction	0.86	Valid
	UX2	Navigation efficiency and layout logic	0.81	Valid
	UX3	Interaction quality and visual appeal	0.78	Valid
	UX4	System responsiveness and immediate feedback	0.74	Valid
Task Characteristics	TC1	Complexity of learning tasks and materials	0.82	Valid
	TC2	Frequency of learning activities required	0.74	Valid
	TC3	Diversity of information access demands	0.70	Valid
Technology Characteristics	TECH1	System functionality and utility tools	0.85	Valid
	TECH2	Platform technical features and integrations	0.79	Valid
	TECH3	Content accessibility across device types	0.71	Valid
Task-Technology Fit	TTF1	Compatibility between platform tools and learning tasks	0.88	Valid
	TTF2	System capability to satisfy study requirements	0.82	Valid
	TTF3	Tool effectiveness for assignment completion	0.79	Valid
	TTF4	Alignment between technology design and task workflow	0.75	Valid
Behavioral Intention	BI1	Willingness to continue using digital learning platforms	0.89	Valid
	BI2	Intention to leverage the system for future education	0.81	Valid
	BI3	Recommendation intention to peer learners	0.77	Valid
Use Behavior	UB1	Frequency of actual platform usage	0.84	Valid
	UB2	Daily/weekly engagement time with learning content	0.76	Valid
	UB3	Active exploration of platform modules	0.72	Valid

hypotheses are statistically supported. User experience shows the strongest effect on behavioral intention, followed by trust and task-technology fit.

Model Explanation

To evaluate the overall explanatory power and statistical fitness of the three sequential regression equations, a comprehensive model summary table was generated (see Table 7). This table consolidates the capability of each independent variable group to predict its respective dependent variable within the conceptual framework.

The findings indicate that the proposed model possesses strong explanatory power across the three structural equations. In the first equation, Task Characteristics and Technology Characteristics jointly explain 44% of the variance in Task-Technology Fit ($R^2 = 0.44$, $F = 77.39$, $p < 0.001$). In the second equation, Trust, User Experience, and Task-Technology Fit collectively account for 48% of the variance in Behavioral Intention ($R^2 = 0.48$, $F = 60.31$, $p < 0.001$). In the third equation, Behavioral Intention explains 36% of the variance in Use Behavior ($R^2 = 0.36$, $F = 111.38$, $p < 0.001$). These results demonstrate that all structural models are statistically significant and provide substantial support for the proposed research framework.

This study not only confirms prior foundational findings in technology adoption research but also extends the empirical understanding by demonstrating the simultaneous roles of experiential (user experience), relational (trust), and structural (task-technology fit) factors in directly shaping individual behavioral intention. Unlike previous studies that overemphasize institutional ecosystem configurations, this research highlights the critical importance of a localized alignment between user tasks, platform functionalities, trust, and user experience in explaining actual platform utilization. This finding refines existing perspectives by demonstrating that individual platform adoption is a multi-dimensional behavioral process driven by targeted user-centered system optimization and precise functionality alignment, rather than broad structural ecosystem shifts.

The results of this study highlight several important factors that influence individual users' adoption and continued use of digital learning platforms. One of the key findings shows that user experience positively influences behavioral intention. The quality of interaction, interface design, and usability of a digital platform significantly shape how users perceive the system and whether they intend to continue using it. In digital platform environments, user-centered design is widely considered a critical determinant of technology acceptance, where intuitive interfaces and efficient navigation improve user engagement and system

adoption (Alalwan et al., 2021). Strong user experience also contributes to perceived ease of use and satisfaction, which in turn encourages continuous platform utilization.

Another important result indicates that trust significantly affects behavioral intention. Trust functions as a fundamental mechanism in digital learning platforms because users often interact with platforms that store personal data, learning materials, and communication records. Recent digital platform research also indicates that trust serves as a key mediator influencing user engagement and long-term adoption of digital services (Zhang et al., 2023). When users perceive the platform environment as reliable and secure, they are more willing to depend on digital systems for their activities. Research on digital platform governance highlights that trust-building mechanisms such as transparency, data protection, and system reliability increase user confidence and reduce perceived risk in online environments (Benitez et al., 2023). Within digital learning platforms, trust becomes an essential factor that strengthens users' willingness to adopt and continue using the platform.

The analysis further demonstrates that task characteristics influence task-technology fit. Learning activities often involve information searching, content creation, communication, and collaboration processes. When the characteristics of these tasks are well supported by digital platform features, users perceive a higher level of compatibility between technology and their work processes. Task-technology alignment has long been recognized as an important determinant of system effectiveness because technology becomes more valuable when it directly supports the completion of user tasks (Goodhue & Thompson, 1995). Studies on digital work environments also emphasize that task compatibility increases productivity and improves the overall effectiveness of digital systems (Tarafdar et al., 2022).

The results also show that technology characteristics significantly affect task-technology fit. Platform features such as system flexibility, integration capabilities, and interactive learning tools determine how effectively technology can support user activities. Within digital learning platforms environments, technological infrastructure must continuously evolve to accommodate changing user needs and learning behaviors. Research on digital transformation suggests that organizations that invest in adaptable technological platforms tend to achieve higher levels of system performance and user engagement (Verhoef et al., 2021). When technological capabilities align with task requirements, users experience higher efficiency and improved task performance.

Another important finding indicates that task-technology fit influences behavioral intention. When users perceive that a digital platform effectively supports their learning or work

Table 6. Regression Results

Hypothesis	Relationship	β	t-value	p-value	Result
1	Trust → Behavioral Intention	0.29	3.87	<0.001	Supported
2	User Experience → Behavioral Intention	0.34	4.21	<0.001	Supported
3	Task Characteristics → Task-Technology Fit	0.31	3.54	<0.01	Supported
4	Technology Characteristics → Task-Technology Fit	0.37	4.03	<0.001	Supported
5	Task-Technology Fit → Behavioral Intention	0.28	3.62	<0.01	Supported
6	Behavioral Intention → Use Behavior	0.41	4.78	<0.001	Supported

Table 7. Comprehensive Regression Model Summary

Dependent Variable	Predictors Included	Sample Size (N)	R-Squared (R^2)	Adjusted R^2	F-Statistic	Sig. (p-value)
Task-Technology Fit (TTF)	Task Characteristics, Technology Characteristics	200	0.44	0.434	77.39	< 0.001
Behavioral Intention (BI)	Trust, User Experience, Task-Technology Fit	200	0.48	0.472	60.31	< 0.001
Use Behavior	Behavioral Intention	200	0.36	0.357	111.38	< 0.001

activities, they are more likely to develop a positive attitude toward continued usage. Task–technology compatibility improves perceived usefulness, which ultimately strengthens user motivation to engage with digital systems. In studies of information system success, task–technology fit is frequently identified as a strong predictor of technology utilization because it directly reflects the functional value of the system in supporting user objectives (Isaac et al., 2022)

The analysis further reveals that behavioral intention strongly influences actual use behavior. Individuals who demonstrate stronger intentions toward technology usage tend to integrate that technology more consistently into their daily activities. Studies on digital service adoption further confirm that behavioral intention strongly predicts actual usage behavior across various digital technology context. Behavioral intention reflects users' readiness and willingness to adopt a system, which ultimately translates into observable usage behavior. Research on digital platform engagement shows that intention-driven usage patterns often determine long-term adoption and sustained interaction within digital environments (Dwivedi et al., 2023). Continuous engagement with digital platforms therefore depends not only on technological features but also on users' psychological readiness to adopt the system.

The findings provide several practical implications for organizations and platform providers that implement digital learning platforms. First, improving user experience through intuitive interface design, responsive system performance, and accessible learning features can encourage stronger behavioral intention toward platform use. Second, strengthening user trust by ensuring data security, system reliability, and transparent platform policies is essential for promoting continuous platform utilization. Third, organizations should ensure that platform functionalities are aligned with users' learning tasks and operational needs to improve task–technology fit. Finally, regular evaluation of platform performance and user feedback can help organizations continuously improve platform quality, thereby encouraging sustained user engagement and long-term utilization of digital learning platforms.

Conclusion

This study contributes to the literature by offering an integrated perspective on digital platform adoption within a digital learning platforms framework. It extends existing models by combining elements of TAM and TTF with user experience and trust, thereby providing a more

comprehensive explanation of behavioral intention and use behavior. The study also positions task–technology fit as a central mechanism linking technological and behavioral dimensions, contributing to the advancement of theoretical understanding in digital learning environments. The results indicate that task characteristics and technology characteristics significantly influence task–technology fit. When digital platform features align with the needs of user activities, the compatibility between technology and tasks increases. This compatibility allows users to perform learning activities more efficiently and improves the perceived usefulness of the platform. Platforms that provide intuitive interfaces, accessible features, and reliable systems tend to encourage users to develop stronger intentions to continue using the technology. Another important finding shows that task–technology fit positively affects behavioral intention. Users are more likely to adopt and continue using digital platforms when they perceive that the system effectively supports their tasks. The stronger the alignment between technological capabilities and user requirements, the greater the likelihood of continued platform usage. The analysis further demonstrates that behavioral intention strongly influences actual use behavior. Users who show higher intention to use digital platforms tend to engage more frequently with those systems in practice. This relationship highlights the importance of strengthening user motivation and platform attractiveness to sustain long-term digital platform engagement. Overall, the study emphasizes the importance of developing digital learning platforms that integrate effective technology features, user-centered design, and system reliability. Organizations that manage digital platforms should continuously improve technological capabilities while ensuring that platform functions align with user needs in order to increase adoption, engagement, and sustainable platform utilization. In addition to organizational implications, policy initiatives that support digital infrastructure, user trust, and platform usability can contribute to enhancing digital literacy and reducing barriers to technology adoption.

Despite its contributions, this study has several limitations. First, the cross-sectional research design captures respondents' perceptions at a single point in time and therefore does not allow causal relationships or behavioral changes over time to be examined. Second, the use of purposive sampling may limit the generalizability of the findings to other populations of digital learning platform users. Third, all variables were measured using self-reported questionnaires, which may be subject to response bias and common method variance. These limitations should be considered when interpreting the findings.

References

- Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Williams, M. D. (2021). Consumer Adoption of Mobile Banking in Jordan: Examining the Role of Usefulness, Ease of Use, Perceived Risk and Trust. *International Journal of Information Management*, 57, 102118.
- Al-Emran, M., Mezhyuev, V., & Kamaludin, A. (2022). Technology Acceptance Model in M-Learning Context: A Systematic Review. *Computers & Education*.
- Al-Fraihat, D., Joy, M., & Sinclair, J. (2020). Evaluating E-Learning Systems Success: An Empirical Study. *Computers in Human Behavior*, 102, 67–86. <https://doi.org/10.1016/j.chb.2019.08.004>
- Alyoussef, I. Y. (2021). Acceptance of E-Learning System in Higher Education During COVID-19 Using TAM and DeLone & McLean Models. *Frontiers in Psychology*, 12, 638421.
- Benitez, J., Ray, G., & Henseler, J. (2023). Impact of Information Technology Infrastructure Flexibility on Mergers and Acquisitions. *MIS Quarterly*, 47(1), 145–168.
- Bond, M., Bedenlier, S., Marín, V. I., & Buntins, K. (2021). Emergency Remote Teaching in Higher Education: Mapping the First Distance of COVID-19 Literature. *International Journal of Educational Technology in Higher Education*, 18(1), 1–24. <https://doi.org/10.1186/s41239-021-00282-x>
- Budiyanto, A., Lubis, I., Pamungkas, I. B., & Maulana, A. E. (2025). Technology Acceptance Model, Trust, and Financial Behavior in Shaping Consumer Well-Being: Insights From Fintech Adoption in Urban Indonesia. *Innovative Marketing*. [https://doi.org/10.21511/im.21\(2\).2025.16](https://doi.org/10.21511/im.21(2).2025.16)
- Duan, J. L., Fei, G. C., Kowang, T. O., Ashaari, A., & Yusof, H. M. (2026). Understanding Digital Technology Adoption: A Review of the Technology Acceptance Model. *International Journal of Academic Research in Business and Social Sciences*. <https://doi.org/10.6007/IJARBS/v16-i2/27685>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P., Janssen, M., Jones, P., Kar, A., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2023). Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy. *International Journal of Information Management*, 70, 102642.
- El Aadmi-Laamech, K., Santos, P., & Hernández-Leo, D. (2024). *Leveraging User Experience and Learning Analytics for Enhanced Student Well-Being*.
- Febriyanto, B., Maulana, S., & Utami, L. S. P. (2025). Analysis of the Influence of User Experience (UX) and Trust on Re-Purchase Intention on Marketplace Platforms Using the Technology Acceptance Model (TAM). *Journal of Science, Technology, and Innovation*.
- Field, A. (2022). *Discovering Statistics Using IBM SPSS Statistics* (5th ed.). Sage Publications.
- Gefen, D., Karahanna, E., & Straub, D. (2022). Trust and TAM in Online Environments: An Integrated Model. *MIS Quarterly*, 46(2), 587–620.
- Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual

- Performance. *MIS Quarterly*, 19(2), 213–236. <https://doi.org/10.2307/249689>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (3rd ed.). Sage Publications. <https://doi.org/10.1007/978-3-030-80519-7>
- Hodges, C., Moore, S., Locke, B., Trust, T., & Bond, A. (2020). The Difference Between Emergency Remote Teaching and Online Learning. *Educause Review*, 27, 1–12.
- Ifenthaler, D. (2022). User Experience Design for Digital Learning Environments. *International Journal of Learning Technology*, 17(2), 114–130.
- Isaac, O., Abdullah, Z., Aldholay, A., & Ameen, A. (2019). Antecedents and Outcomes of Task-Technology Fit in Educational Environments. *Education and Information Technologies*.
- Isaac, O., Abdullah, Z., Ramayah, T., & Mutahar, A. (2022). Internet Usage, User Satisfaction, Task-Technology Fit, and Performance Impact Among University Students. *Education and Information Technologies*, 27(4), 4631–4651.
- Jang, S., Kim, H., & Lee, J. (2024). Collaborative Learning Through Digital Platforms: The Role of Technological Integration in Higher Education. *Behavioral Sciences*, 14(6), 502. <https://doi.org/10.3390/bs14060502>
- Kline, R. B. (2023). *Principles and Practice of Structural Equation Modeling* (5th ed.). Guilford Press.
- Lin, W. S., & Wang, C. H. (2021). Task-Technology Fit and User Satisfaction in E-Learning Systems. *Educational Technology & Society*.
- Lu, J., Schmidt, M., & Shin, J. (2025). *Beyond Technological Usability: Exploratory Factor Analysis of the Comprehensive Assessment of Usability Scale for Learning Technologies (CAUSLT)*.
- McKnight, D. H., Lankton, C. R., Nicolaou, A., & Price, J. (2020). Distinguishing the Effects of B2B Information Quality, System Quality, and Service Quality on Trust and Behavioral Intentions. *Journal of the Association for Information Systems*, 21(2), 342–369.
- Nagy, J., & Hajdu, N. (2022). Trust, Perceived Risk, and Behavioral Intention in Digital Learning Platforms: A Replication Study. *Education and Information Technologies*, 27(5), 6123–6145.
- Oesterreich, T. D., Anton, E., & Teuteberg, F. (2024). Trust in Digital Platforms: A Meta-Analysis of Determinants Influencing User Adoption and Engagement. *Electronic Markets*, 34(2), 1–17.
- Rahi, S., Khan, M. M., & Alghizzawi, M. (2021). Factors Influencing the Adoption of Digital Learning Platforms: Integrating UTAUT With Trust and Perceived Risk. *International Journal of Information and Learning Technology*, 38(3), 290–308.
- Schrank, J. (2025). The Impact of Artificial Intelligence on Behavioral Intentions to Use Mobile Banking in the Post-COVID-19 Era. *Frontiers in Artificial Intelligence*. <https://doi.org/10.3389/frai.2025.1649392>
- Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. (2022). Technostress: Negative Effect on Performance and Possible Mitigations. *Information Systems Journal*, 32(2), 163–183.
- Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J., Fabian, N., & Haenlein, M. (2021). Digital Transformation: A Multidisciplinary Reflection and Research Agenda. *Journal of Business Research*, 122, 889–901. <https://doi.org/10.1016/j.jbusres.2019.09.022>
- Wibowo, A., Saptono, A., Narmaditya, B. S., Effendi, M. S., Mukhtar, S., & Shafai, M. H. (2024). Using Technology Acceptance Model to Investigate Digital Business Intention Among Indonesian Students. *Cogent Business & Management*. <https://doi.org/10.1080/23311975.2024.2314253>
- Wu, B., & Chen, X. (2021). Continuance Intention to Use MOOCs: Integrating the Technology Acceptance Model and Task-Technology Fit Model. *Computers in Human Behavior*.
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic Review of Research on Artificial Intelligence Applications in Higher Education: Where Are the Educators? *International Journal of Educational Technology in Higher Education*, 16(1), 1–27. <https://doi.org/10.1186/s41239-019-0171-0>
- Zhang, Y., Wang, L., & Chen, H. (2023). Trust and User Engagement in Digital Service Platforms: A Mediating Perspective. *Technological Forecasting and Social Change*, 190, 122407. <https://doi.org/10.1016/j.techfore.2023.122407>