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AI-Driven Learning Environments and Learning Flow Experience: The Role of Technological Readiness in Supporting Sustainable Quality Education

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Abstract: This study examines the determinants of learning flow experience in AI-driven learning environments and its contribution to Sustainable Development Goal 4 (Quality Education). A quantitative approach was employed using survey data from 316 undergraduate students experienced in AI-integrated courses across four faculties at Universitas Negeri Padang, Indonesia. The data were analyzed using partial least squares structural equation modeling (SEM-PLS). The results indicate that AI technological readiness has a significant positive effect on learning flow experience and mediates the influence of instructor support, community support, and teaching platform quality on learning flow. In contrast, AI digital literacy does not have a significant effect on technological readiness, indicating that technical training alone is insufficient and cannot independently build learners' readiness without strong pedagogical and contextual support. Furthermore, AI facilitating conditions slightly but significantly strengthen the relationship between technological readiness and learning flow, suggesting their role as a contextual boundary factor. These findings highlight the importance of integrating instructional, technological, and institutional support systems in AI-driven learning. In conclusion, fostering technological readiness through supportive learning ecosystems is essential for promoting meaningful and sustainable learning experiences aligned with SDG 4.

Keywords: AI digital literacy; AI-driven learning; Facilitating conditions; Learning flow experience; Technological readiness

Introduction

The rapid advancement of artificial intelligence (AI) has profoundly transformed contemporary learning environments, reshaping how instructional content is delivered, personalized, and experienced (Hafifah et al., 2025; Wulandari et al., 2025). AI-driven learning systems increasingly leverage adaptive algorithms, learning analytics, and intelligent feedback to support learners' individual needs and optimize learning processes. As a result, educational research has shifted from examining whether AI can be adopted to understanding how AI-enabled environments shape learners' cognitive and experiential outcomes (Holmes et al., 2022; Zawacki-Richter et al., 2019).

Among various learning outcomes, learning flow experience—characterized by deep concentration, enjoyment, and immersion—has gained increasing attention in digital and AI-enhanced learning contexts. Flow has been associated with higher engagement, persistence, and learning effectiveness, particularly in technology-mediated environments where learners interact intensively with digital systems (Hamari et al., 2016; Radianti et al., 2020; Simatupang et al., 2025). However, recent studies suggest that advanced technologies alone do not automatically induce flow; rather, learners' experiences depend on how well they

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can navigate, understand, and meaningfully engage with AI-supported learning systems (Mäntymäki et al., 2020; (Efendi, 2025).

Prior research on AI in education has predominantly focused on technological capabilities, system performance, or adoption intentions, often emphasizing factors such as perceived usefulness, usability, or AI literacy (Dwivedi, 2023; Ng et al., 2021). While these studies provide valuable insights, they tend to adopt a technology-centric perspective that underestimates the role of learners' technological readiness a broader construct encompassing confidence, preparedness, and perceived capability to engage with AI-driven learning environments. Emerging evidence indicates that readiness-related factors play a crucial role in determining whether learners can effectively leverage AI technologies for deep and meaningful learning (Chiu & Churchill, 2023; Ifenthaler & Yau, 2020).

In parallel, a growing body of literature emphasizes that AI-driven learning should be understood as a socio-technical system, in which learning experiences are shaped not only by technology but also by instructional practices, social support, and institutional contexts (Bond et al., 2021; Ouyang et al., 2022). Instructor support and peer interaction remain critical in helping learners interpret AI-generated feedback, manage cognitive demands, and develop confidence in using AI tools. Similarly, the quality of teaching platforms—including interface design, system transparency, and adaptive features—has been shown to influence learners' engagement and perceived control in AI-enhanced learning environments (Hwang & Tu, 2021).

Despite these advances, two key gaps remain in the current literature. Addressing these gaps is important because higher education institutions are increasingly adopting AI-based learning technologies without fully understanding the conditions that enable meaningful learning experiences. Without such understanding, the integration of AI in education risks focusing solely on technological implementation rather than on how students psychologically and pedagogically engage with AI systems (Holmes et al., 2022; Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019).

First, limited empirical research has systematically examined how multiple antecedents—such as AI digital literacy, instructional support, community support, and teaching platforms—jointly influence learning flow experience in AI-driven learning environments through the mechanism of AI technological readiness. Most existing studies investigate these factors in isolation, offering fragmented explanations of learners' experiences. Second, the contextual conditions under which technological readiness translates into optimal learning experiences remain underexplored. Recent studies suggest that facilitating conditions, including institutional support and access to AI resources, may act as boundary factors that amplify or constrain the effects of readiness on learning outcomes (Dwivedi, 2023; Venkatesh et al., 2016), yet empirical evidence in AI-driven educational settings remains scarce.

Addressing these gaps, the present study develops and empirically examines an integrated model to explain learning flow experience in AI-driven learning environments. The study investigates how AI digital literacy, community support, instructor support, and teaching platform quality influence learning flow experience through the mediating role of AI technological readiness. In addition, AI facilitating conditions are incorporated as a moderating factor that may strengthen the relationship between technological readiness and learning flow experience. By integrating individual competence, pedagogical support, and technological infrastructure into a unified framework, this study aims to provide a more comprehensive understanding of how meaningful learning experiences emerge in AI-enhanced educational environments.

By doing so, this study makes several contributions to the literature. Theoretically, it extends contemporary flow-oriented perspectives by integrating technological readiness and facilitating conditions into the explanation of learning experiences in AI-enhanced environments. Empirically, it provides robust evidence on the mechanisms through which social, instructional, and technological factors shape learning flow. Practically, the findings offer actionable insights for educators, instructional designers, and institutions seeking to design AI-driven learning environments that foster immersive and sustainable learning experiences.

Furthermore, conceptual framework this study is grounded in a socio-technical perspective that conceptualizes AI-driven learning as the result of interactions between individual readiness and contextual support. Within this framework, Learning Flow Experience (LFE) is positioned as the primary outcome, representing learners' optimal psychological state characterized by concentration, enjoyment, and immersion during AI-supported learning activities. Achieving flow in AI-enhanced environments requires not only exposure to technology but also learners' preparedness to engage with AI systems meaningfully.

AI Technological Readiness (AIR) is conceptualized as a central mechanism that mediates the effects of multiple antecedent factors on learning flow experience. AIR reflects learners' psychological preparedness and willingness to engage with AI technologies in learning activities, including their confidence, comfort, and openness toward integrating AI tools into learning processes. Unlike AI Digital Literacy (AIL), which represents learners' knowledge and technical capability to understand and operate AI technologies, technological readiness reflects a broader attitudinal condition that captures learners' motivation and readiness to meaningfully adopt these technologies in learning contexts. Four exogenous variables—AI Digital Literacy (AIL), Community Support (CS), Instructor Support (IS), and Teaching Platform (TP)—are proposed as key drivers of AIR, representing individual competence, social support, pedagogical guidance, and technological quality, respectively. Furthermore, AI Facilitating Conditions (FC) are incorporated as a moderating variable, reflecting institutional and infrastructural support that may strengthen the impact of technological readiness on learning flow experience.

The moderating role of AI Facilitating Conditions (FC) is particularly important in understanding how technological readiness translates into learning flow experience. Facilitating conditions refer to the availability of institutional support, reliable infrastructure, and accessible technological resources that enable students to effectively use AI-based learning systems. Even when students demonstrate a high level of AI Technological Readiness (AIR), inadequate facilitating conditions such as unstable internet connectivity, limited platform accessibility, or insufficient technical support—may hinder the transformation of readiness into an optimal learning experience. Conversely, when facilitating conditions are adequate, they can enhance the effectiveness of students' technological readiness by allowing learners to interact with AI systems more smoothly and without technical barriers. In this context, facilitating conditions function as an enabling environment that strengthens the relationship between AIR and Learning Flow Experience (LFE), allowing students' readiness to fully translate into deeper engagement and immersive learning experiences.

As shown in Figure 1, the conceptual framework of this study integrates AI digital literacy, instructor support, community support, and teaching platform as antecedents of AI technological readiness. AI technological readiness is positioned as a central mediating variable that influences learning flow experience. In addition, facilitating conditions are incorporated as a moderating variable that may strengthen the relationship between technological readiness and learning flow experience.

Based on the conceptual framework illustrated in Figure 1, several hypotheses are proposed, encompassing direct, mediating, and moderating relationships, all of which are grounded in a strong theoretical foundation. AI Digital Literacy reflects learners' ability to understand, critically evaluate, and effectively interact with AI technologies. Recent studies suggest that AI-related literacy enhances learners' confidence and reduces uncertainty when engaging with intelligent learning systems, thereby fostering greater readiness to adopt AI-based tools for learning (Hwang et al., 2023; Ng et al., 2021). Learners who possess higher levels of AI digital literacy are more likely to perceive AI technologies as manageable and beneficial, which contributes to their technological readiness. Therefore, the following hypothesis is proposed: H1: AI Digital Literacy (AIL) has a positive effect on AI Technological Readiness (AIR).

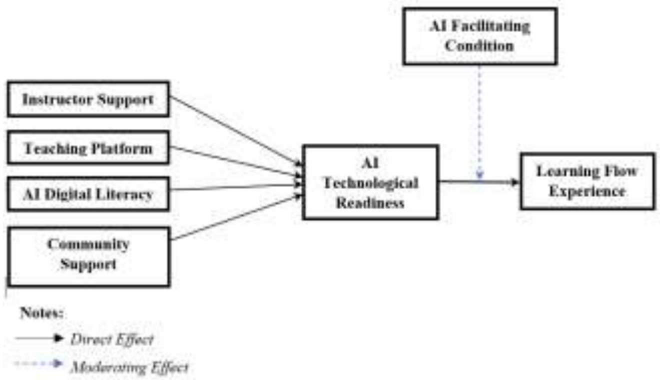

Figure 1. Conceptual Framework

AI Technological Readiness is considered a critical antecedent of optimal learning experiences in technology-enhanced environments. Prior research indicates that learners' readiness to use advanced digital technologies positively influences engagement, immersion, and intrinsic motivation—key characteristics of learning flow (Li et al., 2021; Shin et al., 2019). In AI-driven learning contexts, readiness enables learners to allocate cognitive resources toward learning tasks rather than technological management, facilitating deeper flow experiences. Accordingly, the following hypothesis is formulated: H2: AI Technological Readiness (AIR) has a positive effect on Learning Flow Experience (LFE).

Learning in AI-driven environments is embedded within social contexts. Community support, manifested through peer interaction, trust, and collaborative learning, has been shown to enhance learners' confidence and willingness to engage with digital technologies (Bond et al., 2020; Dede et al., 2019). Supportive learning communities can reduce feelings of isolation and uncertainty, thereby strengthening learners' technological readiness in AI-supported learning settings. Thus, the following hypothesis is proposed: H3: Community Support (CS) has a positive effect on AI Technological Readiness (AIR).

Despite the increasing role of AI, instructor support remains essential in shaping learners' readiness to engage with AI-based learning technologies. Empirical evidence suggests that instructional guidance, feedback, and emotional support significantly reduce technology-related anxiety and enhance learners' perceived competence in digital learning environments (Howard et al., 2021; Kim et al., 2022). In AI-enhanced learning, instructor support is expected to facilitate learners' understanding and effective use of AI tools, leading to higher technological readiness. Therefore, the following hypothesis is advanced: H4: Instructor Support (IS) has a positive effect on AI Technological Readiness (AIR).

The quality of teaching platforms plays a crucial role in shaping learners' perceptions and readiness toward AI-driven learning. Well-designed platforms characterized by high usability, reliability, and service quality have been shown to reduce cognitive load and enhance users' sense of control, which contributes to greater technological readiness (Al-Fraihat et al., 2020; Feziyasti & Ashel, 2025; Zhang et al., 2022). In AI-supported learning environments, platform quality is expected to function as a structural enabler of readiness. Hence, the following hypothesis is proposed: H5: Teaching Platform (TP) has a positive effect on AI Technological Readiness (AIR).

Additionally, recent research emphasizes that contextual and individual factors often influence learning outcomes indirectly through learners' psychological and technological readiness (Scherer et al., 2019; Zhai et al., 2023). In AI-driven learning environments, AI Technological Readiness is expected to mediate the effects of AI Digital Literacy, Community Support, Instructor Support, and Teaching Platform quality on learning flow experience. These antecedent factors may not directly induce flow; instead, they enhance learners' readiness, which subsequently enables immersive learning experiences. Based on this rationale, the following mediation hypotheses are proposed: H6: AI Technological Readiness (AIR) mediates the relationship between AI Digital Literacy (AIL) and Learning Flow Experience (LFE). H7: AI Technological Readiness (AIR) mediates the relationship between Community Support (CS) and Learning Flow Experience (LFE). H8: AI Technological Readiness (AIR) mediates the relationship between Instructor Support (IS) and Learning Flow Experience (LFE). H9: AI Technological Readiness (AIR) mediates the relationship between Teaching Platform (TP) and Learning Flow Experience (LFE).

Moreover, the relationship between technological readiness and learning outcomes may depend on the availability of supportive institutional and infrastructural conditions. Facilitating conditions—such as access to AI resources, technical support, and system compatibility—have been identified as key contextual factors that strengthen the effectiveness of technology adoption and use (Mohd Rahim et al., 2022; Venkatesh et al., 2016). In AI-enhanced learning environments, favorable facilitating conditions are expected to amplify the positive effect of AI technological readiness on learning flow experience. Therefore, the following moderating hypothesis is proposed: H10: AI Facilitating Conditions (FC) positively moderate the relationship between AI Technological Readiness (AIR) and Learning Flow Experience (LFE).

This study offers a novel contribution by positioning AI technological readiness as a central mechanism that connects instructional, social, and technological factors to students' learning flow experience within a socio-technical framework. While prior research on AI-supported learning has largely focused on technological capabilities or digital literacy, relatively little attention has been paid to learners' readiness to meaningfully engage with AI systems. By emphasizing readiness as a critical psychological and contextual construct, this study provides a deeper understanding of how students translate technological opportunities into immersive learning experiences.

Furthermore, this research incorporates AI facilitating conditions as a boundary factor, offering a more comprehensive explanation of how individual readiness interacts with institutional infrastructure and organizational support to shape learning outcomes in AI-driven environments. This study is particularly important given the rapid adoption of artificial intelligence in higher education, which has outpaced scholarly understanding of how such technologies foster meaningful and sustainable learning engagement. By addressing this gap, the study contributes to ongoing efforts to support the achievement of Sustainable Development Goal 4 (Quality Education) through the effective integration of AI in educational settings.

Method

This study employed a quantitative research design using a cross-sectional survey to examine the determinants of learning flow experience in AI-driven learning environments. A structural equation modeling approach based on partial least squares (SEM-PLS) was adopted to test the proposed research model. SEM-PLS was considered appropriate given its suitability for theory development, predictive modeling, and the analysis of complex relationships involving mediating and moderating effects (Hair et al., 2019).

Purposive sampling was used to select respondents who had experience in AI-integrated learning environments, such as courses utilizing AI-supported learning tools or intelligent digital learning platforms.

The sample consisted of 316 undergraduate students from four faculties at Universitas Negeri Padang, namely the Faculty of Tourism and Hospitality, Faculty of Engineering, Faculty of Mathematics and Natural Sciences, and Faculty of Social Sciences. These faculties were selected due to their active integration of digital and AI-supported learning, ensuring that participants had relevant exposure to AI-driven learning.

In terms of faculty distribution, approximately 26% of respondents were from the Faculty of Tourism and Hospitality, 29% from the Faculty of Engineering, 23% from the Faculty of Mathematics and Natural Sciences, and 22% from the Faculty of Social Sciences. Regarding gender, the sample comprised 58% female and 42% male students. The majority of respondents were aged between 18 and 22 years (approximately 72%), followed by those aged 23–25 years (21%) and above 25 years (7%).

Data were collected using an online questionnaire distributed through institutional communication channels. Participation was voluntary, and respondents were informed of the anonymity and confidentiality of their responses. All collected data were screened for completeness and consistency prior to analysis.

All constructs in this study were measured using validated instruments adapted from prior studies published in reputable international journals. The adaptation process involved minor contextual modifications to ensure relevance to AI-driven learning environments while preserving the original conceptual meanings of each construct.

The adapted instruments underwent a content validation process through expert judgment involving subject matter and language experts to ensure clarity, relevance, and contextual appropriateness. In addition, a pilot test was conducted with a small group of students to assess the initial reliability and comprehensibility of the measurement items. The results indicated that all items were well understood and met acceptable reliability criteria, supporting their use in the full-scale data collection.

All measurement items were assessed using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). AI Technological Readiness (AIR) was measured using five items adapted from Falebita & Kok (2024), capturing learners' enthusiasm toward AI, awareness of AI applications, comfort in using AI technologies, time commitment, and perceived benefits of AI for learning. Instructor Support (IS) was assessed through seven items adapted from Kim et al. (2022), reflecting cognitive support, emotional encouragement, and autonomy support provided by instructors in AI-supported learning contexts. Teaching Platform (TP) was measured using six items adapted from Zhang et al. (2022), focusing on the technical quality, content quality, and service quality of AI-enabled learning platforms. AI Digital Literacy (AIL) consisted of seven items adapted from Hwang et al. (2023), encompassing learners' critical comprehension of AI, awareness of its social impact, practical technology use, and ethical considerations related to AI adoption. Community Support (CS) was measured using six items adapted from Rovai (2002), assessing learners' sense of connectedness, trust, and peer academic support within the learning community. AI Facilitating Conditions (FC) were measured using five items adapted from Mohd Rahim et al. (2022), covering institutional infrastructure, access to AI resources, technology compatibility, availability of technical support, and organizational encouragement for AI use. Finally, Learning Flow Experience (LFE) was assessed using six items adapted from Li et al. (2021), capturing learners' concentration, intrinsic motivation, enjoyment, and immersion during AI-driven learning activities. In addition, demographic information, including field of study, gender, and age, was collected to describe the characteristics of the respondents (Cunningham, 2023; Eagly, 2013).

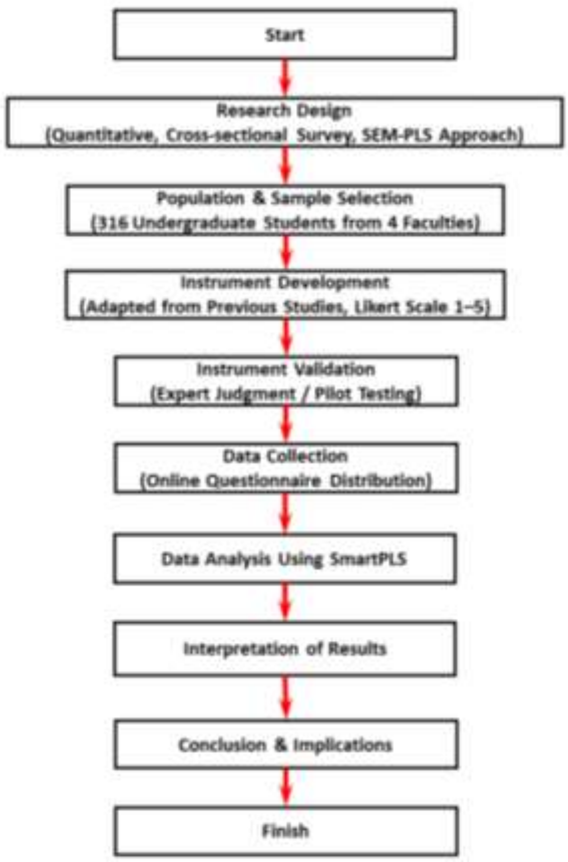

Figure 2. Research Procedure Flowchart

Data analysis was conducted using SmartPLS software following a two-stage analytical procedure. To assess the potential for common method bias (CMB), Harman's single-factor test was conducted. The results indicated that a single factor did not account for the majority of the variance, as the total variance explained by the first factor was below the 50% threshold, suggesting that common method bias is not a serious concern in this study. In addition, a full collinearity assessment was performed by examining the variance inflation factor (VIF) values, and all values were found to be below the recommended threshold of 3.3, further confirming the absence of common method bias.

First, the measurement model was evaluated by assessing indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, with indicators below the recommended outer loading threshold excluded to ensure measurement quality. Second, the structural model was assessed by examining path coefficients, t-values, p-values, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). Bootstrapping with 10,000 resamples was applied to obtain more stable and robust estimates of the significance of direct, mediating, and moderating effects, while the moderating role of AI facilitating conditions was examined using an interaction term approach in accordance with recent SEM-PLS methodological recommendation (Hair et al., 2019).

This study adhered to ethical research standards. Participation was voluntary, informed consent was obtained from all respondents, and no personally identifiable information was collected. The data were used solely for research purposes and analyzed in aggregate form. The overall research procedure is summarized in Figure 2, which illustrates the sequential stages from research design and data collection to data analysis using SEM-PLS.

Result and Discussion

The measurement model was assessed in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The results indicate that the majority of indicator loadings exceeded the recommended threshold of 0.70, demonstrating satisfactory indicator reliability. A limited number of indicators with outer loadings below the recommended threshold (AIL7, IS7, LFE4, TP4) were excluded from further analysis to ensure adequate indicator reliability. Following this refinement, all retained indicators demonstrated satisfactory loadings, and the measurement model met the criteria for internal consistency reliability and convergent validity.

Internal consistency reliability was confirmed, as Cronbach's alpha values ranged from 0.857 to 0.956, while composite reliability values ranged from 0.891 to 0.966, exceeding the recommended minimum of 0.70 for all constructs. These results suggest strong internal consistency across the measurement scales.

Convergent validity was established, with all constructs achieving average variance extracted (AVE) values above the threshold of 0.50, ranging from 0.541 to 0.851. This indicates that each construct explains more than half of the variance of its indicators. The complete results are reported in Table 1.

Table 1. Measurement Model.

Measurement Items		Outer Loading	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Digital Literacy (AIL)	AIL1	0.773	0.857	0.891	0.541
	AIL2	0.726			
	AIL3	0.797			
	AIL4	0.769			
	AIL5	0.746			
	AIL6	0.733			
AI Technological Readiness (AIR)	AIR1	0.853	0.907	0.93	0.728
	AIR2	0.821			
	AIR3	0.869			
	AIR4	0.867			
	AIR5	0.854			
Community Support (CS)	CS1	0.751	0.857	0.893	0.582
	CS2	0.73			
	CS3	0.815			
	CS4	0.773			
	CS5	0.777			
	CS6	0.729			
AI Facilitating Condition (FC)	FC1	0.955	0.956	0.966	0.851

Measurement Items		Outer Loading	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
	FC2	0.894			
	FC3	0.877			
	FC4	0.93			
	FC5	0.952			
Instructor Support (IS)	IS1	0.727	0.873	0.902	0.57
	IS2	0.81			
	IS3	0.832			
	IS4	0.743			
	IS5	0.759			
	IS6	0.762			
Learning Flow Experience (LFE)	LFE1	0.884	0.891	0.922	0.675
	LFE2	0.901			
	LFE3	0.862			
	LFE5	0.879			
	LFE6	0.888			
Teaching Platform (TP)	TP1	0.843	0.864	0.899	0.598
	TP2	0.855			
	TP3	0.81			
	TP5	0.727			
	TP6	0.715			

Discriminant validity was initially assessed using the Fornell–Larcker criterion (see Table 2). The results indicate that most constructs met the required criteria; however, a potential overlap was observed between Learning Flow Experience and AI Facilitating Conditions, as the correlation between these constructs slightly exceeded the square root of the AVE. To further assess discriminant validity, the Heterotrait-Monotrait ratio (HTMT) was examined. All HTMT values were below the recommended threshold of 0.90, indicating that discriminant validity was established despite the limitations observed in the Fornell–Larcker criterion.

Table 2. Fornell Larcker Criterion

	AIL	AIR	CS	FC	IS	LFE	TP
AIL	0.736						
AIR	0.626	0.853					
CS	0.692	0.549	0.763				
FC	0.444	0.285	0.549	0.922			
IS	0.715	0.653	0.601	0.354	0.755		
LFE	0.517	0.434	0.667	0.858	0.443	0.821	
TP	0.719	0.658	0.584	0.334	0.736	0.413	0.773

The overall model fit was evaluated using the standardized root mean square residual (SRMR) and the normed fit index (NFI). The SRMR values for both the saturated model (0.115) and the estimated model (0.117) exceed the commonly recommended threshold, indicating a relatively modest model fit. In addition, the NFI value (0.409) is considerably below the conventional benchmark, suggesting limited improvement of the proposed model compared to the null model. However, in variance-based SEM approaches such as PLS-SEM, model fit indices are not the primary criteria for model evaluation. This study adopts an exploratory and predictive perspective, where greater emphasis is placed on the model's explanatory and predictive capabilities, including path coefficients, R^2 values, and effect sizes (Hair et al., 2019). Therefore, despite the relatively low model fit indices, the model is considered acceptable for theory development and prediction-oriented analysis. The results of model fit are presented in Table 3.

Table 3. Model Fit

	Saturated model	Estimated model
SRMR	0.115	0.117
d_ULS	12.017	12.305
d_G	21.284	21.263
Chi-square	12549.71	12607.3
NFI	0.409	0.406

For testing the hypothesis, the structural model was assessed by examining path coefficients, t-values, p-values, and effect sizes (f^2). The results demonstrate that AI Technological Readiness (AIR) has a significant positive effect on Learning Flow Experience (LFE) ($\beta = 0.236$, $p < 0.001$), with a moderate effect size, highlighting the central role of technological readiness in facilitating optimal learning experiences in AI-driven environments.

Regarding the antecedents of AI Technological Readiness, Community Support ($\beta = 0.160$, $p = 0.004$), Instructor Support ($\beta = 0.269$, $p = 0.002$), and Teaching Platform ($\beta = 0.228$, $p = 0.024$) were found to have significant positive effects on AIR. Among these predictors, Instructor Support demonstrated the strongest influence, followed by Teaching Platform and

Community Support. In contrast, AI Digital Literacy did not exhibit a statistically significant direct effect on AIR (β = 0.136, p = 0.108), suggesting that digital literacy alone may be insufficient to enhance technological readiness without supportive contextual factors. The results of direct hypothesis test are reported in Table 4.

Table 4. Direct Hypothesis Test

Hypothesis		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	f-square	Hypothesis Decision
H1	AIL -> AIR	0.136	0.137	0.084	1.61	0.108	0.01	Rejected
H2	AIR -> LFE	0.236	0.235	0.042	5.627	0.001	0.202	Supported
H3	CS -> AIR	0.16	0.163	0.056	2.857	0.004	0.025	Supported
H4	IS -> AIR	0.269	0.272	0.086	3.128	0.002	0.041	Supported
H5	TP -> AIR	0.228	0.225	0.101	2.258	0.024	0.021	Supported

In addition, the mediating role of AI Technological Readiness was examined using bootstrapping procedures. The results indicate that AIR significantly mediates the relationships between Community Support and Learning Flow Experience (β = 0.038, p = 0.018), Instructor Support and Learning Flow Experience (β = 0.064, p = 0.007), and Teaching Platform and Learning Flow Experience (β = 0.054, p = 0.037). These findings suggest that social, instructional, and technological supports enhance learning flow indirectly by strengthening learners' readiness to engage with AI-based learning systems.

Conversely, the indirect effect of AI Digital Literacy on Learning Flow Experience via AIR was not statistically significant (β = 0.032, p = 0.128), indicating the absence of a mediating mechanism for this relationship. Mediating hypothesis test are reported in Table 5.

Table 5. Mediating Hypothesis Test

Hypothesis		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothesis Decision
H6	AIL -> AIR -> LFE	0.032	0.032	0.021	1.523	0.128	Rejected
H7	CS -> AIR -> LFE	0.038	0.039	0.016	2.359	0.018	Supported
H8	IS -> AIR -> LFE	0.064	0.064	0.024	2.684	0.007	Supported
H9	TP -> AIR -> LFE	0.054	0.053	0.026	2.09	0.037	Supported

Furthermore, the moderating effect of AI Facilitating Conditions on the relationship between AI Technological Readiness and Learning Flow Experience was also examined. The interaction effect between AIR and Facilitating Conditions was found to be positive and statistically significant (β = 0.076, p = 0.044), with a small but meaningful effect size. This result indicates that the positive impact of technological readiness on learning flow is strengthened under favorable facilitating conditions, such as adequate infrastructure, institutional support, and access to AI-related resources. Moderated hypothesis tests are provided in Table 6.

Table 6. Moderated Hypothesis Test

Hypothesis		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	f-square	Hypothesis Decision
H10	FC x AIR -> LFE	0.076	0.077	0.046	1.974	0.044	0.024	Supported

Overall, this study provides empirical insights into the determinants of learning flow experience in AI-driven learning environments by integrating technological readiness and facilitating conditions into a unified explanatory framework. Overall, the findings suggest that learning flow in AI-supported contexts is not merely driven by exposure to advanced technologies, but rather emerges from the interaction between learners' preparedness and supportive instructional and institutional ecosystems. This perspective aligns with recent conceptualizations of AI-driven education as a socio-technical system, where human, pedagogical, and organizational factors play a decisive role in shaping learning (Artha et al., 2024; Bond et al., 2021; Zawacki-Richter et al., 2019).

AI Technological Readiness as a Central Mechanism

One of the most salient findings of this study is the significant role of AI technological readiness in predicting learning flow experience. Learners who perceive themselves as ready to engage with AI-supported learning systems are more likely to experience sustained concentration, enjoyment, and immersion during learning activities. Recent studies in AI-enhanced education suggest that readiness-related factors such as confidence, perceived competence, and adaptive capacity are critical antecedents of deep engagement and optimal learning experiences (Agyemang Adarkwah et al., 2025; Ifenthaler & Yau, 2020; Setiaji et al., 2025).

From a contemporary theoretical standpoint, this finding extends recent reinterpretations of flow in digital learning environments, which argue that flow is contingent upon learners' ability to manage technological complexity and align cognitive demands with available resources (Hamari et al., 2016; Riasani et al., 2025). In AI-driven learning contexts, insufficient readiness may divert cognitive resources toward system navigation and problem-solving, thereby constraining the emergence of flow states.

Beyond its direct effect, AI technological readiness acts as a key mediating variable that explains how instructional support, community support, and teaching platform quality influence learning flow experience. Specifically, these factors enhance learners' readiness to engage with AI technologies, which in turn leads to more immersive and optimal learning experiences. This finding is consistent with recent technology adoption research emphasizing readiness as a proximal determinant of engagement and learning outcomes in advanced digital environments (Chiu & Churchill, 2023; Tsai et al., 2020).

Social and Instructional Support as Drivers of Readiness

The significant indirect effects of community support and instructor support on learning flow experience through AI technological readiness underscore the fundamentally social and pedagogical nature of AI-driven learning. Despite the increasing autonomy afforded by AI technologies, learners continue to rely on social interaction, guidance, and feedback to develop confidence and readiness to engage effectively with AI systems. This aligns with earlier in the Community of Inquiry framework, which emphasize that social presence and teaching presence are foundational in sustaining meaningful learning experiences in technology-mediated environments. Recent empirical evidence further suggests that social presence and instructional support remain essential for reducing uncertainty and fostering productive engagement in AI-enhanced learning environments (Arini & Nursa'ban, 2024; Bond et al., 2021).

Instructor support emerged as a particularly strong predictor of technological readiness, highlighting the evolving but not diminishing—role of educators in AI-supported education. This finding is consistent with prior research by Vygotsky & Cole (1978), which underscores the importance of guided support and scaffolding in advancing learners' capabilities within their zone of proximal development. Contemporary studies indicate that instructors serve as critical mediators between learners and AI systems by scaffolding AI use, contextualizing feedback, and addressing ethical or cognitive concerns related to AI adoption (Holmes et al., 2022; Ouyang & Jiao, 2021). Thus, AI-driven learning should be viewed not as a replacement of instructional roles, but as a context in which pedagogical expertise becomes even more consequential.

The Role of Teaching Platforms in AI-Driven Learning

The significant contribution of teaching platforms to AI technological readiness further highlights the importance of system design, usability, and integration. This perspective is consistent with earlier work in the Technology Acceptance Model, which emphasizes perceived ease of use and perceived usefulness as key determinants of users' readiness to engage with technology. In addition, highlights through the Cognitive Theory of Multimedia Learning that well-designed instructional interfaces can reduce cognitive load and enhance meaningful learning. Recent research on AI-enabled learning platforms further emphasizes that intuitive interfaces, adaptive features, and transparent AI functionalities can reduce cognitive burden and enhance learners' sense of control, thereby supporting immersive learning experiences (Hwang & Tu, 2021; Karim et al., 2025). In this sense, teaching platforms function not merely as delivery tools but as structural enablers that facilitate learners' transition from initial engagement to sustained flow experiences.

This finding resonates with recent extensions of technology acceptance and learning experience models, which increasingly focus on experiential quality and learner–system interaction rather than solely on perceived usefulness or ease of use (Al-Samarraie et al., 2020; Kuswanti et al., 2024; Radianti et al., 2020).

Rethinking the Role of AI Digital Literacy

Interestingly, AI digital literacy did not demonstrate a significant effect on AI technological readiness. This finding indicates that technical competence related to AI does not automatically translate into learners' readiness to engage with AI-driven learning systems. While digital literacy reflects learners' understanding of AI concepts and their ability to operate AI tools, technological readiness represents a broader psychological condition that involves willingness, confidence, and motivation to integrate these technologies into learning activities. Without adequate pedagogical guidance and structured learning experiences, technical competence alone may not be sufficient to foster readiness for AI-driven learning environments.

This distinction between technical competence and contextual readiness has been increasingly emphasized in recent AI education literature, which argues that learners require not only operational skills but also instructional guidance, social interaction, and institutional support to meaningfully engage with AI technologies (Holmes et al., 2022; Ng et al., 2021; Ouyang et al., 2022; Puspitasari et al., 2024). Therefore, the findings suggest that digital literacy may function as a basic prerequisite rather than a determining factor in shaping technological readiness. Instead, readiness appears to be more strongly influenced by pedagogical support, collaborative learning environments, and well-designed AI-enabled platforms that provide the contextual conditions necessary for meaningful engagement with AI technologies.

Facilitating Conditions as a Contextual Amplifier

The significant moderating effect of AI facilitating conditions further reinforces the contextual nature of learning flow in AI-driven environments. Although the moderating effect is relatively small, the results indicate that facilitating conditions slightly but significantly strengthen the relationship between AI technological readiness and learning flow experience. When learners operate within supportive institutional contexts—characterized by adequate infrastructure, access to AI tools, and organizational encouragement—the translation of technological readiness into learning flow becomes more likely. This finding aligns with recent adaptations of unified technology acceptance frameworks, which emphasize facilitating conditions as contextual boundary factors shaping learning outcomes in complex digital ecosystems (Dwivedi, 2023; Venkatesh et al., 2016).

In AI-enhanced learning contexts, facilitating conditions appear to function as an environmental catalyst, enabling learners to convert readiness into immersive and sustained learning experiences rather than fragmented or superficial engagement. Among these conditions, stable internet access, ease of platform accessibility, and the availability of technical support emerge as the most critical elements in supporting effective AI-driven learning. When these components are inadequate, students may struggle to translate their readiness into meaningful learning experiences. Conversely, well-established facilitating conditions allow learners to fully leverage their technological readiness, resulting in deeper engagement and sustained learning flow.

Theoretical Implications

Taken together, these findings contribute to the growing body of literature on AI-driven learning in several ways. First, this study advances contemporary understandings of learning flow by empirically demonstrating the central role of AI technological readiness in AI-enhanced environments. Second, it integrates individual readiness and contextual facilitating conditions into a unified explanatory model, offering a more holistic account of how learning flow emerges in AI-driven education. Finally, by revealing the limited role of AI digital literacy, the study challenges skill-centric assumptions and supports a shift toward context-sensitive and readiness-oriented perspectives in AI education research.

Future Research

Future research is recommended to further explore the role of AI digital literacy in different learning contexts and populations, particularly by examining its interaction with pedagogical design and instructional strategies. In addition, longitudinal studies are needed to capture the dynamic development of technological readiness over time. Future studies may also incorporate additional variables such as learner motivation, self-regulated learning, and emotional engagement to provide a more comprehensive understanding of learning flow in AI-driven environments. Furthermore, expanding the research to diverse institutional settings and disciplines would enhance the generalizability of the findings.

Conclusion

This study examined the determinants of learning flow in AI-driven learning environments by integrating technological readiness and facilitating conditions into a unified model. The findings reveal that AI technological readiness plays a central role in enhancing learning flow, both directly and as a mediator linking instructional support, community support, and teaching platforms to learning experiences. In contrast, AI digital literacy was not a significant predictor, indicating that technical skills alone are insufficient without pedagogical and instructional support. Additionally, AI facilitating conditions were found to modestly strengthen the relationship between technological readiness and learning flow, emphasizing the role of institutional support and infrastructure. Theoretically, this study extends flow-based learning perspectives by incorporating technological readiness and contextual factors, while practically highlighting the need for balanced development of instructional support, platform design, and institutional readiness in AI-driven education. Future research should further explore these relationships using longitudinal or experimental designs.

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Author Contributions
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Conflicts of Interest
The authors declare no conflict of interest.

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