

## PAPER

# User Readiness and AI Integration as Drivers of Smart Nano Learning in Mobile Environments

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## ABSTRACT

Lifelong learning has been undergoing a significant transformation driven by the development of digital learning platforms and the leveraging of artificial intelligence (AI) to personalize learning experiences. This study aims to examine the factors influencing the readiness of smart nano-learning platforms to support lifelong learning, with particular emphasis on user readiness, trust, and AI support as key determinants. Additional contributing factors considered include content quality, user experience, learning environment, and data systems and reporting. A quantitative research design was employed, with 378 undergraduate students using a validated and reliable questionnaire. The data were analyzed using structural equation modeling (SEM). The results indicate that user readiness, trust, and AI have significant direct effects on the smart nano-learning platform's readiness. The findings suggest that the effective design of platforms for lifelong learning must integrate both human-centered factors and intelligent technological support. In particular, strengthening learners' readiness and trust, alongside the strategic use of AI to enable scalable, personalized learning, is essential for developing sustainable, effective smart nano-learning platforms for real-world lifelong learning contexts.

## KEYWORDS

smart nano-learning, interactive mobile learning, lifelong learning, user readiness and trust (URT), artificial intelligence (AI) support in education

## 1 INTRODUCTION

Lifelong learning is now a foundational element of the knowledge society in the digital era. UNESCO has promoted the concept of a learning society, highlighting the necessity for individuals to engage in continuous learning throughout their lives. Digital innovations facilitate equitable access to education and skill development across all age groups [1]. This global transformation is primarily driven by rapid technological advancements, especially in artificial intelligence (AI), which has shown significant potential to personalize learning processes and tailor

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instructional content to individual learners. These developments enhance both the quality and effectiveness of education [2]. In higher education, open, flexible, and accessible learning models have become essential mechanisms for fostering lifelong learning capacity.

Recent bibliometric evidence on mobile learning in higher education further indicates a significant global shift from technology-supported content delivery toward intelligent, personalized, and lifelong learning-oriented ecosystems. The evolution of mobile learning research reveals increasing integration of AI, learning analytics, and flexible learning infrastructures designed to support continuous and ubiquitous learning across diverse learner populations [3]. This trend highlights that contemporary mobile learning environments are no longer confined to supplementary learning tools but are becoming a central mechanism for transforming higher education into a lifelong learning system. Such a transformation provides an important theoretical foundation for emerging models such as smart nano-learning, which extend mobile learning into highly adaptive, learner-centered, and scalable formats.

Smart nano-learning is a recent educational innovation designed to reflect contemporary learning behaviors. It provides highly focused content in very short segments, typically lasting 2–5 minutes, which is significantly shorter than traditional microlearning modules of 15–30 minutes [4]. Nano-learning allows learners to participate in educational activities during brief periods of availability and supports ubiquitous learning on mobile devices at any time and place. This method has rapidly gained popularity, paralleling the widespread use of social media platforms such as TikTok and YouTube Shorts for distributing short-form educational content [5]. Empirical research indicates that short video content can be an effective supplementary learning tool for university students. However, its effectiveness is strongly influenced by content credibility and the quality of learner–content interaction, both of which significantly affect learners' attitudes and intentions to use nano-learning platforms [5, 6]. Although previous studies confirm the pedagogical value of nano-learning via short-form videos, they also emphasize the need for developers to address content quality, trustworthiness, and interaction design, as these elements directly impact learners' acceptance and continued use of nano-learning platforms. These observations align with the concept of user readiness, which suggests that learners are more likely to adopt new educational technologies when they have adequate skills, confidence, and trust in both the content and the system.

Contemporary nano-learning platforms are increasingly designed as intelligent systems that integrate AI and learning analytics to better support personalized learning experiences. Such systems can dynamically adapt learning pathways based on learners' prior knowledge and learning pace, recommend subsequent content tailored to individual needs, and provide automated feedback when learners encounter difficulties. AI-driven learning platforms thus play a critical role in enabling personalization and delivering timely, targeted feedback that enhances learning effectiveness [8]. For example, Baillifard et al. [9] reported that students supported by AI tutors, which can monitor learners' understanding and adjust practice tasks, accordingly, achieved learning outcomes up to 15 percentile points higher than those without AI support, particularly among undergraduate students who tend to respond positively to flexible systems with personalized recommendation features. At a broader level, meta-analytic evidence indicates that AI use in higher education significantly improves students' academic performance, particularly when it supports self-directed learning beyond the classroom [10].

Although advanced technologies are essential for the success of learning platforms, user-related factors ultimately determine platform readiness (PR) and adoption. Even highly sophisticated platforms may not achieve widespread use if learners

lack basic digital skills or do not trust the system. [7] highlighted that students' confidence and trust are critical human factors influencing the acceptance of AI-based educational technologies, both directly and indirectly. Trust in AI directly impacts perceived usefulness and indirectly affects students' readiness to engage with AI-supported learning systems. Additionally, user experience (UX) factors, such as ease of initial use and intuitive interface design, are crucial in shaping users' perceptions of platform usefulness and their intention to continue using digital systems. Technology acceptance models, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), consistently indicate that effort expectancy, or the perceived ease of learning to use a system, positively influences technology adoption and continued usage intentions. Platforms with clear navigation and user-friendly interfaces are more likely to generate positive user experiences and favorable attitudes, whereas poorly designed or overly complex systems can lead to dissatisfaction and reduced intention to continue using [11].

In this context, the present study investigates the key factors influencing the readiness of smart nano-learning platforms to support lifelong learning. The research focuses on two primary drivers: user readiness and trust (URT), and AI support, which are conceptualized as central determinants of platform readiness. Additional factors considered include content quality, user experience, learning environment, and data systems and reporting, all of which may contribute to perceived platform readiness. This study employs a quantitative methodology, utilizing a questionnaire-based survey and structural equation modeling (SEM) to examine causal relationships among these factors and the readiness of smart nano-learning platforms for lifelong learning.

## 2 LITERATURE REVIEW

This literature review synthesizes six principal determinants that influence the readiness of smart nano-learning platforms: (1) content quality (CQ), (2) UX, (3) learning environment (LE), (4) data systems and reporting (DSR), (5) AI support, and (6) URT. Additionally, it provides a conceptual clarification of PR within the broader framework of intelligent lifelong learning.

### 2.1 CQ

Content quality in nano-learning is both essential and complex, as it requires balancing conciseness with conceptual adequacy within limited time frames. Effective nano-learning content should address a single, clearly defined learning objective per unit to minimize cognitive overload. Although each unit is brief, the content must be sequenced coherently and connected to form a comprehensive knowledge structure, thereby reducing the risk of superficial learning. Segmentation (dividing content into manageable units) and weeding (removing non-essential information) are widely recognized strategies for optimizing learners' attention, retention, and comprehension. Vivekananth [12] demonstrated that the effectiveness of small learning units is closely linked to objective-focused content design, modular structuring that facilitates stepwise learning, and the removal of extraneous elements that may distract learners. These principles are fundamental to high-quality content development for learning platforms, especially in higher education and professional training. Furthermore, adaptive content structures that remain concise while aligning with learners' needs can enhance learning outcomes and adaptability.

When nano-learning content meets these criteria, PR increases because high-quality content can be scaled and maintained to support continuous, long-term learning.

## 2.2 UX

High-quality UX is a primary determinant of a platform's functional readiness. Intuitive, stable, and responsive platforms tend to increase user satisfaction and promote sustained engagement. Extensive research identifies usability and perceived ease of use as strong predictors of learners' intentions to adopt and continue using educational platforms. In the context of the TAM and the UTAUT, effort expectancy—the degree to which users perceive a system as requiring minimal effort to learn and operate—positively influences users' intentions for continued use. User-centered design is also critical for improving UX [13]. Hasani et al. [14] demonstrated that e-learning platforms designed to meet users' needs significantly influence interaction behaviors and overall learning experiences. Similarly, Alterkait and Alduaij [15] found that learners assess their experiences based on the quality of information and content, which is closely linked to satisfaction with platform use. Therefore, enhancing UX requires a focus on ease of use, system stability, and adaptive design to ensure that diverse user groups can engage effectively and consistently with the platform.

## 2.3 LE

An effective online LE must foster learner engagement and support a sense of belonging within a digital learning community. Social presence, defined as the perceived authenticity of interpersonal interactions among learners and instructors, is widely recognized as a key component of high-quality online learning. Gao et al. [16] demonstrated that online environments promoting social interaction significantly enhance learners' motivation and learning effectiveness. Interactions between learners and instructors, as well as among peers, are positively associated with online learning performance, with social presence and engagement mediating this association. Meaningful interaction strengthens learners' sense of connection and involvement, thereby improving learning outcomes [17]. Limbu and Pham [18] also found that interaction in online learning supports engagement and increases time spent on self-study. Consistent with these findings, Shehzad and Charles [19] emphasized that well-designed online instruction and instructor communication enhance learners' perceived connectedness and engagement. An effective LE should support both individual and socially mediated learning. Providing opportunities for discussion, collaboration, and peer exchange can enhance self-regulation skills and sustain a sense of community despite geographic separation. Designing platforms to facilitate collaborative learning is a critical aspect of pedagogical readiness, indicating that a platform prepared for real-world use must enable both self-directed and collaborative learning.

## 2.4 DSR

Learning DSR dashboards are essential for converting learners' behavioral data into actionable insights for both learners and instructors, often utilizing learning analytics and educational data mining. Platforms with advanced DSR capabilities can monitor and visualize learner progress in real time, deliver timely feedback, and enable instructors to adjust instructional strategies or provide targeted support efficiently.

For example, well-designed dashboards can present learners' participation, attendance, and assessment outcomes, allowing learners to track progress and plan learning strategies effectively. Instructors can use these data to refine instruction in alignment with learners' needs. Cabi and Türkoglu [20] observed that analytic outputs from data systems inform the development of tools that support data-driven learning. In higher education, dashboards are increasingly important for instructional decision-making. Recent advancements include the integration of AI into dashboards to predict learning difficulties and automatically recommend improvement strategies. Evidence indicates that AI-driven dashboards enhance reporting capabilities and support learners' self-regulation more effectively [21]. A robust, well-designed DSR strengthens a platform's capacity for continuous monitoring and iterative improvement, which is essential for lifelong learning, where sustained development is expected.

## 2.5 AI support

Artificial intelligence plays a crucial role in enabling intelligent learning platforms to serve large and diverse learner populations with heterogeneous needs. In nano-learning contexts, AI can facilitate high levels of personalization by recommending lessons or subsequent courses that match learners' interests and proficiency levels, automatically adjusting task difficulty based on learner capability, answering questions or providing immediate explanations, and generating automated feedback to address individual learning weaknesses. In this sense, AI functions as an intelligent tutoring layer that supports individual learners alongside human instructors. Research indicates that appropriately designed AI can increase learners' motivation and overall engagement [22, 23]. From an instructional perspective, AI is commonly conceptualized as an augmentation mechanism rather than a replacement for teachers, as it can reduce workload and enable instructors to support larger cohorts while maintaining individualized guidance [24]. Merino-Campos [25] reported that AI influences higher education learning in multiple domains, including academic performance, personalized learning experiences, and engagement, outcomes that align with the broader objectives of lifelong learning. When AI-enabled personalization is implemented in higher education, it can adapt content, learning activities, and instructional approaches to individual learners, contributing to more effective learning and improved experiences, particularly in individual or small-group learning contexts. This aligns closely with the nature of nano-learning, which is characterized by frequent short learning episodes requiring ongoing scaffolding and reinforcement. Consequently, scalable AI systems that can extend individualized support to large learner populations are a core condition for PR at the institutional and societal levels, as they enable platforms to accommodate diverse learners while sustaining personalized learning, which is arguably the central goal of intelligent lifelong learning platforms.

## 2.6 URT

User-related factors are fundamental to platform success. Regardless of how well a system is designed, a platform is unlikely to achieve sustained impact if users are not ready to use it or do not trust it. A substantial body of technology acceptance research suggests that trust is a complex psychological factor that serves as a stabilizing mechanism, linking usage intention to effective, sustained use. Without trust, even users who initially intend to adopt a technology may discontinue use before

they have had a chance to engage meaningfully. Bentley et al. [26] developed an instrument to measure learners' trust in AI-enabled educational technologies and found that trust influences perceived usefulness both directly and indirectly through learners' readiness to use AI. Put differently, learners who trust AI-based technologies tend to perceive such tools as more useful, and trust can also strengthen learners' readiness to engage with AI, thereby increasing acceptance. Similarly, Walter [27] examined how teachers develop trust in educational AI technologies and reported that trust can be enhanced through improved AI literacy and skill development. As trust increases, teachers' intentions to use AI-supported systems also rise. Trust was significantly associated with perceived usefulness, concern levels, and attitudes toward AI. These findings highlight URT as a foundational condition that platform designers must prioritize. By strengthening users' skills, confidence, and trust, developers can increase the likelihood of sustained platform use, thereby improving the platform's readiness for real-world deployment. In summary, a learning platform is ready to support lifelong learning only if users are prepared and willing to trust it and continue using it over time.

## 2.7 Smart nano-learning PR for lifelong learning

Platform readiness refers to the extent to which an intelligent learning platform is perceived as sufficiently prepared and capable of supporting lifelong learning effectively and sustainably, primarily from the user's perspective. This construct reflects users' evaluations of how well a platform can meet their long-term learning needs. In the present study, PR is operationalized through multiple dimensions, including the platform's capacity to support personalized learning, its overall suitability for lifelong learning, its usability and flexibility, its appropriateness for institutional implementation, and its potential for broader societal scalability. Collectively, these dimensions indicate that the platform is ready for widespread adoption to promote learning across the lifespan.

**Table 1.** An integrated conceptual framework linking theoretical foundations and research variables of a smart nano-learning platform

| Research Variable | Core Concept  | Related Theoretical Foundations                            | Role in the Model  |
|-------------------|---|--|--|
| CQ                | Concise and focused content design; reduction of cognitive load     | Cognitive Load Theory; Segmentation and Weeding Principles | Enhances learning effectiveness, ensures knowledge continuity, and supports nano-learning delivery   |
| UX                | Ease of use, system stability, and user satisfaction                | TAM; UTAUT; User-Centered Design                           | Determines usage intention and user acceptance of the platform                                       |
| LE                | Interaction, engagement, sense of social presence                   | Social Presence Theory; Community of Inquiry Framework     | Fosters learner engagement, collaborative learning atmosphere, and sustained participation           |
| DSR               | Learning analytics, feedback mechanisms, and dashboards             | Learning Analytics Framework; Educational Data Mining      | Supports personalized learning, informed decision-making, and learner and instructor self-regulation |
| AI                | Personalized recommendations, reinforcement, and automated feedback | AI Readiness; Adaptive Learning Systems                    | Enables personalized learning, enhances efficiency, and expands platform capability                  |
| URT               | Skills, confidence, trust in the system, and AI                     | Trust Theory in Technology; AI Acceptance Models           | Determines technology acceptance and sustained, effective use  |
| PR                | Capacity to support lifelong learning                               | Technology Success Models; Lifelong Learning Frameworks    | Primary research outcome reflecting the long-term usability and scalability of the platform          |

Based on a comprehensive literature review and theoretical analysis, this study identifies six key determinants that are expected to influence the readiness of smart nano-learning platforms to support lifelong learning: content quality, user experience, learning environment, data systems and reporting, AI support, and URT. These determinants are grounded in both technological perspectives and human behavioral theories and are synthesized into an integrated conceptual framework that guides the formulation of causal hypotheses, as presented in Table 1.

To examine the relationships between these determinants and platform readiness, the study adopts a quantitative research design. Data are collected through a questionnaire-based survey administered to users of online learning platforms, and the resulting data are analyzed using SEM. SEM is particularly suitable for this study as it enables the examination of complex causal relationships among multiple latent constructs within the proposed integrated framework.

### 3 METHODS

A quantitative research design was employed, utilizing a questionnaire-based survey and SEM to examine the causal relationships among the proposed constructs. The methodological procedures are outlined below.

#### 3.1 Sampling

The sample size was determined based on the requirements of covariance-based structural equation modeling (CB-SEM), which necessitates sufficient observations to ensure stable maximum likelihood estimation, adequate statistical power, and reliable model fit indices. Given that the research model included seven latent variables measured by 35 observed indicators, both measurement and structural model complexity were considered. SEM literature indicates that models with numerous indicators and moderate expected factor loadings require larger sample sizes to reduce estimation bias and instability. Therefore, the target sample size was set at a minimum of 400 respondents, which is appropriate for CB-SEM analysis using LISREL and ensures robust parameter estimates.

#### 3.2 Data collection

A structured questionnaire was developed based on the proposed conceptual framework and relevant literature. The instrument measured perceptions of six latent constructs: CQ, UX, LE, DSR, AI support, and URT. All items were rated on a five-point Likert scale, from 5 (strongly agree) to 1 (strongly disagree), with each construct comprising approximately five items. Content validity was assessed by three subject-matter experts, and internal consistency reliability was evaluated using a pilot sample of 30 respondents. Cronbach's alpha coefficients ranged from 0.82 to 0.90, indicating strong internal consistency across all constructs.

Data were collected using an online questionnaire distributed via Google Forms to undergraduate students. Respondents were informed of the study's purpose and provided informed consent prior to participation (see Section 3.4 for ethical considerations). At the end of the data collection period, 378 fully completed questionnaires were received, resulting in a response rate of approximately 94.5%, which was sufficient for subsequent SEM analysis.

### 3.3 Data analysis

The analysis process began with data screening and cleaning, during which incomplete responses and cases with implausible response patterns were excluded. Preliminary assessments of data quality were then conducted, including tests of normality and sample adequacy using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s test of sphericity. The results indicated a KMO value exceeding 0.80 and a statistically significant Bartlett’s test ( $p < .001$ ), confirming that the data were suitable for factor analysis.

Confirmatory Factor Analysis (CFA) was conducted to validate the measurement model and assess whether the observed indicators accurately represented their respective latent constructs. The analysis, performed using LISREL with maximum likelihood estimation, demonstrated that all seven constructs had significant factor loadings, with standardized loadings above 0.60 and statistical significance at  $p < .001$ . The measurement model exhibited good fit to the data, as indicated by established thresholds ( $\chi^2/df < 3$ , CFI  $> 0.95$ , RMSEA  $< 0.05$ ). These results support the adequacy of the measurement model and its alignment with the theoretical framework.

After validating the measurement model, SEM was used to examine the effects of the six independent latent variables (CQ, UX, LE, DSR, AI, and URT) on PR. The initial structural model specified direct causal paths from each independent variable to PR and allowed intercorrelations among the independent variables to reflect theoretical relationships. Model estimation was conducted using LISREL, with overall fit assessed through multiple goodness-of-fit indices. The initial model did not fit the empirical data adequately. Modification indices were reviewed, and theoretically justified adjustments were made by permitting correlations between error terms of indicators with closely related content. The revised model demonstrated excellent fit ( $\chi^2 = 0.09$ ,  $df = 1$ ,  $p = .759$ , GFI = 1.00, AGFI = .998, RMR = .000, RMSEA = .000), indicating that the structural model effectively explains the covariance structure of the data. Path coefficients and associated statistical values were then recorded for interpretation.

### 3.4 Conflict of interest and research ethics

This study was approved in accordance with the research ethics announcement of Nakhonratchasima Rajabhat University (No. HE-152-2568, June 23, 2025). Participation was entirely voluntary, and all respondents provided informed consent via an online consent form before completing the questionnaire. Participants were informed about the study’s objectives, data collection procedures, confidentiality measures, and protections for anonymity. No personally identifiable information was collected, and all data was used solely for research purposes and reported only in aggregate form. Participants were free to withdraw from the study or decline to answer any question without penalty or adverse consequences.

### 3.5 Limitations of the study

Several limitations should be acknowledged. First, the study relied on self-report measures, which may be subject to response bias, including over- or underestimation of participants’ perceptions. Second, the research employed a cross-sectional design, capturing data at a single point in time and thus limiting the ability to observe changes in user perceptions or behaviors over time. Third, the sample was restricted

to undergraduate students in Thailand, whose learning cultures and digital skills may differ from those of adult learners or learners in other national contexts; therefore, generalizing the findings should be done with caution. Finally, although the model incorporated six key independent variables, other factors, such as institutional policy support or organizational readiness, were not included and may also influence platform readiness. These factors warrant consideration in future research.

## 4 RESULT

### 4.1 Sample characteristics

The sample consisted of 378 undergraduate students drawn from a wide range of academic disciplines, including both science- and social science-oriented programs. The majority of respondents were aged 18–22 years, with female students accounting for 55% of the sample. Most participants were enrolled in their third year of study (60%). In addition, a large proportion of respondents (90%) reported prior experience using their university’s e-learning system or other online learning platforms, with 45% indicating regular weekly use.

### 4.2 Results of structural equation modeling

After examining model fit and implementing the modifications described in the methodology section, Table 1 summarizes the standardized direct effects of the six determinants on smart nano-learning PR, together with their associated error terms and significance levels, as illustrated in Figure 1.

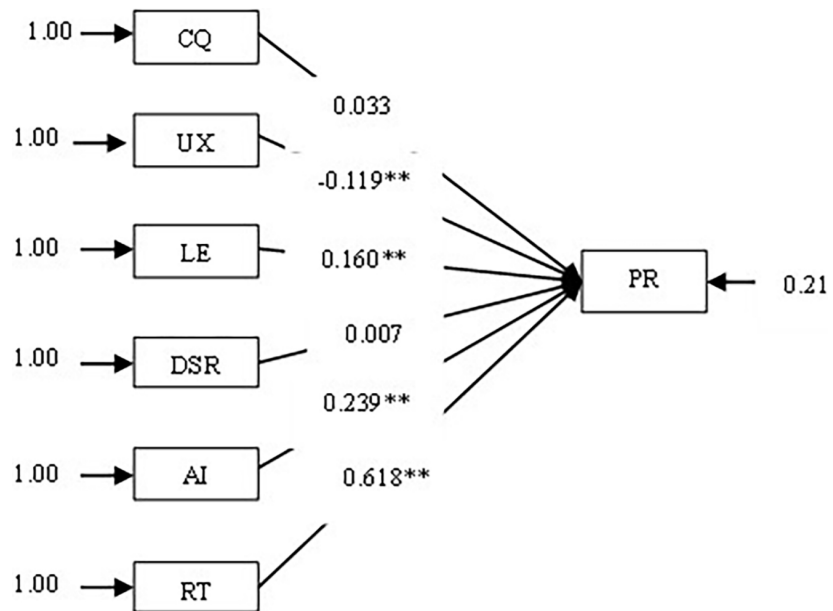


Fig. 1. Structural model of smart nano-learning PR for lifelong learning

The results of the effect-size analysis on PR for lifelong learning are presented below.

User Readiness and Trust exerted the strongest direct influence on platform readiness, with a standardized path coefficient of  $\beta = 0.618$  ( $p < .01$ ). This finding

indicates that higher levels of user skills, confidence, and trust in both the system and AI significantly enhance perceptions of the platform's readiness to support lifelong learning.

AI Support demonstrated the second-strongest direct effect on PR ( $\beta = 0.239$ ,  $p < .01$ ). This result suggests that users who perceive the platform as providing appropriate AI-driven guidance and assistance are more likely to evaluate it as ready for lifelong learning. AI features such as adaptive content delivery, personalized learning pathways, and immediate responses to learner inquiries shape perceptions of the platform's capacity to support long-term learning effectively.

The Learning Environment also exhibited a statistically significant positive direct effect on PR ( $\beta = 0.160$ ,  $p < .01$ ). This indicates that online learning environments promote engagement, interaction, and social connectedness while minimizing feelings of isolation and positively influencing users' perceptions of platform readiness. Platforms that incorporate features enabling discussion, peer interaction, or collaborative activities are more likely to be perceived as suitable for sustained, long-term learning engagement.

In contrast, UX showed a small but statistically significant negative direct effect on PR ( $\beta = -0.119$ ,  $p < .01$ ). This finding suggests that, when other factors are held constant, users with higher levels of technological experience or digital skills may evaluate PR slightly less favorably. One plausible interpretation is that more experienced users tend to hold higher expectations regarding advanced system functionalities; when these expectations are not fully met, perceived readiness may decline. Conversely, users with lower levels of experience do not appear to be disadvantaged when adequate AI and a supportive LE are provided, enabling even novice users to engage with the platform smoothly. Nevertheless, the magnitude of this negative effect is relatively small, indicating limited practical significance and warranting further investigation in future research.

Content Quality exhibited a small positive coefficient ( $\beta = 0.033$ ), but the effect was not statistically significant ( $p > .05$ ). This result indicates that CQ alone did not directly influence PR in the proposed model. Rather than suggesting that CQ is unimportant, this finding implies that high-quality content may function as a baseline or hygiene factor that users inherently expect. While inadequate CQ may hinder platform adoption, high-quality content alone appears insufficient to sustain readiness without complementary human and intelligent support mechanisms.

Similarly, DSR yielded a near-zero coefficient ( $\beta = 0.007$ ) and was not statistically significant ( $p > .05$ ). This suggests that the presence of dashboards or reporting systems alone does not significantly improve users' perceptions of platform readiness. Users may regard reporting features as standard components of learning platforms, similar to content quality. However, it is important to note that DSR is correlated with other determinants in the model, such as AI support, user readiness, and trust. Examining only direct effects may therefore underestimate the indirect role of data systems in shaping UX and learning effectiveness, as discussed further in the discussion section.

Collectively, the six independent variables explained a substantial proportion of the variance in platform readiness, accounting for 79% of the variance (Adjusted  $R^2 = 0.790$ ). This high explanatory power indicates that the proposed model effectively captures the key determinants of smart nano-learning platform readiness. In addition, all goodness-of-fit indices, including chi-square, GFI, AGFI, RMR, and RMSEA, fell within excellent thresholds (as reported in the methodology section), confirming the adequacy and validity of the structural model in explaining the relationships among the determinants and platform readiness, as summarized in Table 2.

**Table 2.** Results of SEM

| Path                 | Coefficient ( $\beta$ ) | Relationship | Significance | Interpretation   |
|----------------------|-------------------------|--------------|--------------|--|
| RT $\rightarrow$ PR  | 0.618                   | Positive     | $p < .01$    | Users with high readiness and trust in the system and AI perceive the platform as more ready.                    |
| AI $\rightarrow$ PR  | 0.239                   | Positive     | $p < .01$    | Perceiving that AI systems provide appropriate support contributes to a higher perception of platform readiness. |
| LE $\rightarrow$ PR  | 0.16                    | Positive     | $p < .01$    | Learning environments that foster interaction and engagement enhance perceived platform readiness.               |
| UX $\rightarrow$ PR  | -0.119                  | Negative     | $p < .01$    | Users with higher experience may have higher expectations, leading to a slightly lower perception of readiness.  |
| CQ $\rightarrow$ PR  | 0.033                   | Positive     | ns           | Content quality alone does not significantly affect perceived platform readiness.                                |
| DSR $\rightarrow$ PR | 0.007                   | Positive     | ns           | Having only reporting systems does not significantly influence users' perception of platform readiness.          |

When examining the magnitude of effects across variables, URT emerged as the strongest direct determinant of platform readiness. This finding indicates that as users' skills, understanding, and confidence in both the system and AI increase, the perceived readiness of smart nano-learning platforms for lifelong learning improves significantly. The second strongest predictor was AI, underscoring the critical role of AI-driven guidance, reinforcement, and adaptive learning in enhancing platform readiness. In addition, the LE exerted a moderate but significant positive influence, suggesting that interactive, engaging, and socially supportive learning environments substantially contribute to users' perceptions of system readiness.

In contrast, UX demonstrated a small but statistically significant negative effect, indicating that even users with limited prior technological experience can perceive themselves as ready to use smart nano-learning platforms when sufficient AI and a supportive LE are in place. Meanwhile, CQ and DSR showed positive but statistically non-significant effects, suggesting that these factors function primarily as foundational platform components rather than as behavioral or usage-driven catalysts when considered alongside human and AI-related determinants.

Overall, the findings indicate that the readiness of smart nano-learning platforms for lifelong learning is not driven solely by technical or content-related quality. Instead, it is predominantly shaped by user-centered factors, particularly URT, along with intelligent support mechanisms and an engaging learning environment. This pattern reflects the evolving nature of contemporary learning platforms, which increasingly emphasize intelligent technologies combined with learner-centered design principles.

## 5 DISCUSSION

The findings of this study provide meaningful insights into the key drivers of readiness for smart nano-learning platforms from the perspective of higher education

students. Among all examined factors, URT exerted the strongest positive influence on PR ( $\beta = 0.618$ ), highlighting the central role of user trust and attitudes toward AI-enabled educational technologies in shaping technology acceptance. High URT reflects not only users' technical competence but also their positive attitudes toward the system, enabling them to engage with the platform confidently and without hesitation or anxiety.

This result aligns with the findings of Nguyen et al. [17], who demonstrated that learner trust directly influences perceived usefulness and intention to use AI-based educational technologies. It also resonates with the work of Ahn [28], who conceptualized trust not merely as an outcome of system use but as a foundational precondition for sustained engagement in AI-supported educational environments. From a practical standpoint, these findings suggest that educational institutions and platform developers should prioritize user preparedness by offering digital skills training, introductory workshops, and accessible, user-friendly guides. Moreover, transparency and reliability in AI systems are essential for strengthening user trust. The present study supports the argument that investing in user readiness may yield greater returns than focusing solely on technological advancements.

AI Support emerged as the second most influential determinant of PR ( $\beta = 0.239$ ), underscoring AI's role as a key enabler of next-generation learning platforms. This finding is consistent with Xia et al. [22], who reported increased learner engagement when AI systems provided personalized recommendations and feedback. AI facilitates scalable personalization, which lies at the core of nano-learning and lifelong learning paradigms. Similarly, Merino-Campos [25] concluded that AI in higher education enhances individualized learning experiences and improves academic outcomes. In this study, students who perceived the platform as offering effective AI-based support were more likely to consider it ready for long-term use in learning. This reinforces the notion that AI capabilities have become a defining feature, enhancing platform attractiveness and perceived readiness [29]. Consequently, platform developers should invest in robust AI integration, such as intelligent recommendation systems, conversational chatbots, and advisory dashboards, while ensuring ethical design and transparency to maintain user trust.

The Learning Environment also demonstrated a significant positive effect on PR ( $\beta = 0.160$ ), emphasizing the importance of interaction and engagement in online learning contexts. This finding is consistent with prior studies highlighting the role of social presence and interaction design in sustaining learner engagement [16, 19]. Despite their familiarity with digital technologies, contemporary students continue to value social connectedness with peers and instructors. Features such as discussion forums, peer feedback mechanisms, online communities, and instructor interaction contribute to perceptions of a vibrant and supportive learning environment, which in turn promotes sustained use of the platform. Accordingly, platform providers should incorporate collaborative learning features, such as discussion groups, group activities, badges, or leaderboards, to foster engagement and strengthen users' emotional attachment to the platform.

Interestingly, UX showed a small but statistically significant negative effect ( $\beta = -0.119$ ), contrary to the conventional expectation that positive UX invariably enhances adoption. One plausible explanation is that less experienced users may be more open to adopting new platforms when sufficient support mechanisms, particularly AI assistance and a supportive learning environment, are in place. In such cases, limited prior experience does not constitute a barrier to readiness. Conversely, highly experienced users may hold higher expectations and standards, leading them to evaluate new platforms more critically unless advanced functionalities meet or

exceed those of existing systems. This pattern aligns with Expectation–Confirmation Theory, which posits that experienced users generally set higher comparison standards. When a new system does not meet these complex expectations, dissatisfaction and reduced readiness to adopt the system may result [30]. The negative effect may also indicate a limitation of the UX measurement instrument used in this study, which primarily emphasized usability rather than hedonic and semantic values. These dimensions are often regarded as more important by experienced users. This interpretation aligns with prior research on resistance to change, which suggests that familiarity with established systems may reduce willingness to adopt new technologies unless clear advantages are perceived. Importantly, this finding does not diminish the importance of UX; rather, it suggests that UX functions as a necessary baseline rather than a primary driver of readiness when AI and social learning features are salient. Developers should therefore strive to balance simplicity and functional depth, offering intuitive interfaces while retaining advanced features for experienced users.

Finally, CQ and DSR did not demonstrate statistically significant direct effects on platform readiness. These factors may represent baseline expectations that users assume as standard features of learning platforms. Platforms lacking adequate CQ or progress-tracking systems are unlikely to be adopted in the first place; however, once these baseline conditions are met, incremental improvements may not significantly influence perceptions of readiness. Within educational contexts, the non-significant effect of CQ suggests that it serves as a necessary baseline rather than a primary motivator for adopting new technologies [31]. Pedagogically, users appear to prioritize the interactional quality of AI systems over static content, given the widespread accessibility of knowledge resources in the digital era. As a result, PR is now more frequently evaluated based on the system's capacity to process information, personalize learning experiences, and address individual learner needs [32]. This finding is consistent with Alterkait and Alduaij [15], who reported that while information quality contributes to satisfaction, sustained usage often depends on additional motivational and engagement-related factors. Moreover, the value of DSR may become more salient for users already committed to self-improvement, whereas dashboards alone may not be decisive adoption triggers. These results suggest that platform developers should maintain high standards of content and data systems while simultaneously investing in motivational and engagement-enhancing features to attract and retain users over time.

While this study focused on university students in Thailand, its findings have significant implications for global and professional development contexts. In the context of lifelong learning, digital skills and trust in technology are now central to human capital development in the 21st century [2]. The smart nano-learning readiness model introduced in this study, which prioritizes trust and AI-supported learning environments, may be applicable to multinational organizations aiming for rapid upskilling and reskilling through bite-sized learning content. This approach is gaining considerable momentum in Europe and North America [33]. Additionally, the adaptability of nano-learning systems offers a viable solution for developing countries seeking to address educational inequality through accessible, personalized innovations [34].

These findings also reflect the broader transformation of higher education toward digitally innovative and cloud-enabled learning ecosystems. Transformative learning environments are increasingly defined by scalable intelligent infrastructures that enable continuous access, real-time interaction, and adaptive learning pathways for diverse learners [35]. From this perspective, the readiness of smart

nano-learning platforms identified in this study can be interpreted as an early indicator of an institution's capacity to participate in digitally transformed lifelong learning systems, where AI functions as a cognitive support layer, user readiness represents human capital preparedness, and interactive learning environments provide the social and pedagogical conditions for sustained engagement. Therefore, PR extends beyond a technological condition and becomes a systemic marker of digital innovation strategy in higher education, in which intelligent technologies, cloud-based scalability, and learner empowerment operate as mutually reinforcing components of transformative learning.

Overall, the findings strongly support the central premise that user-related factors and AI are pivotal in driving the readiness of smart nano-learning platforms for lifelong learning. Platforms must be intelligent and adaptive to individual learners while also fostering trust, engagement, and social interaction. This study contributes empirical evidence relevant to higher education institutions developing learning platforms for students and the public. To ensure long-term platform viability, stakeholders should prioritize user preparedness, AI-enabled capability enhancement, and the design of interactive learning environments while also maintaining high-quality content and accurate data systems.

## 6 CONCLUSION

This study empirically validated user readiness and AI as key drivers of smart nano-learning PR for lifelong learning. Using quantitative data from 378 undergraduate students and SEM, the six factors examined explained about 79% of the variance in platform readiness. User readiness, trust, and AI were the strongest predictors.

The implications of these findings are clear: the development of digital learning platforms should not focus solely on technological sophistication or content quality. Instead, equal, if not greater, attention must be given to preparing users for effective engagement. Users with high levels of digital readiness and trust are better positioned to fully leverage platform capabilities, enabling platforms to achieve their intended educational outcomes. At the same time, well-designed AI integration, characterized by alignment with user needs, accuracy, and transparency, serves as a critical accelerator, enhancing platform adoption and sustained use, thereby transforming nano-learning platforms into effective lifelong learning tools.

These results align with global trends toward learner-centered, AI-driven education, in which learners are active participants and AI enhances both learner and system capabilities. Nevertheless, this study represents only an initial step, and several important challenges remain. Future research should explore more refined approaches to measuring user readiness, potentially incorporating dimensions such as psychological readiness, motivation, and AI-related anxiety or confidence. Further investigation is also needed into the design of AI systems that foster trust and transparency. In addition, extending this study to other populations, such as working adults or secondary school students, would provide valuable comparative insights into how the determinants of PR may vary across learner groups.

In conclusion, the readiness of smart nano-learning platforms to support lifelong learning depends on a synergistic integration of intelligent technologies and prepared users, each reinforcing the effectiveness of the other. Advancing such platforms requires not only technical innovation but also sustained investment in user empowerment. Together, these elements form the foundation for truly

effective smart learning platforms that support lifelong learning and contribute to the development of a sustainable learning society.

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## 8 REFERENCES

- [1] UNESCO, “Fostering a culture of lifelong learning in the digital era,” UNESCO, 2024. [Online]. Available: <https://www.unesco.org/en/articles/fostering-culture-lifelong-learning-digital-era>
- [2] OECD, “OECD digital education outlook 2023: Towards an effective digital education ecosystem,” Paris, France, 2023. <https://doi.org/10.1787/c74f03de-en>
- [3] A. D. Samala, S. Papadakis, and S. Rawas, “Global insights into mobile learning in higher education: A PRISMA-guided bibliometric analysis from 2007 to 2023,” *International Journal of Educational Reform*, 2025. <https://doi.org/10.1177/10567879251341869>
- [4] E. Ang *et al.*, “Analyzing the factors affecting nano-learning behavior of college students on TikTok,” in *Proceedings of the 33rd International Conference on Computers in Education. Asia-Pacific Society for Computers in Education*, 2025. [Online]. Available: <https://library.apsce.net/index.php/ICCE/article/view/6028>
- [5] N. Dunn, “TikTok statistics: The TikTok stats and facts you need to know about,” *Charle Agency*, 2024. [Online]. Available: <https://www.charleagency.com/articles/tiktok-statistics/>
- [6] W. Diteeyont and H.-Y. Ku, “Competency levels and influential factors of college students’ mobile learning readiness in Thailand,” *Smart Learning Environments*, vol. 10, no. 44, pp. 1–20, 2023. <https://doi.org/10.1186/s40561-023-00266-6>
- [7] T. Nazaretsky, P. Mejia-Domenzain, V. Swamy, J. Frej, and T. Käser, “The critical role of trust in adopting AI-powered educational technology for learning: An instrument for measuring student perceptions,” *Computers and Education: Artificial Intelligence*, vol. 8, p. 100368, 2025. <https://doi.org/10.1016/j.caeai.2025.100368>
- [8] W. K. Monib, A. Qazi, R. A. Apong, J. H. Santos, and M. M. Mahmud, “The MIND model: A microlearning AI-integrated instructional design for enhanced learning outcomes,” *Scientific Reports*, vol. 15, Art. no. 41020, pp. 1–14, 2025. <https://doi.org/10.1038/s41598-025-24910-y>
- [9] A. Baillifard, M. Gabella, P. B. Lavenex, and C. S. Martarelli, “Effective learning with a personal AI tutor: A case study,” *Education and Information Technologies*, vol. 30, pp. 297–312, 2025. <https://doi.org/10.1007/s10639-024-12888-5>
- [10] L. Sun and L. Zhou, “Does generative artificial intelligence improve the academic achievement of college students? A meta-analysis,” *Journal of Educational Computing Research*, vol. 62, no. 7, pp. 1676–1713, 2024. <https://doi.org/10.1177/07356331241277937>
- [11] M. M. Soares, T. Ahrām, and C. Falcão, “Usability and user experience,” in *Handbook of Usability and User-Experience*. Boca Raton, FL, USA: CRC Press, 2022, pp. 3–22. <https://doi.org/10.1201/9780429343490-2>
- [12] P. Vivekananth, “Nanolearning: A new paradigm shift in teaching and learning,” *International Journal of Engineering and Management Research*, vol. 12, no. 1, pp. 112–114, 2022. <https://doi.org/10.31033/ijemr.12.1.14>

- [13] R. Li and M. Li, "Teaching strategies and implementation paths for interactive mobile learning platforms in higher education," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 20, pp. 84–98, 2025. <https://doi.org/10.3991/ijim.v19i20.58433>
- [14] L. M. Hasani, I. D. Sensuse, and R. R. Suryono, "User-centered design of e-learning user interfaces: A survey of the practices," in *3rd International Conference on Computer and Informatics Engineering (IC2IE)*, 2020. <https://doi.org/10.1109/IC2IE50715.2020.9274623>
- [15] A. M. Alterkait and Y. M. Alduaij, "Impact of information quality on satisfaction with e-learning platforms: Moderating role of instructor and learner quality," *Sage Open*, vol. 14, no. 1, pp. 1–13, 2024. <https://doi.org/10.1177/21582440241233400>
- [16] F. Gao, C. Wang, H. Xie, and J. Hong, "Social interaction and online learning efficiency for middle school students: The mediating role of social presence and learning engagement," *Behavioral Sciences*, vol. 14, no. 10, pp. 1–18, 2024. <https://doi.org/10.3390/bs14100896>
- [17] T. V. Nguyen, S. Yaghmour, C. S. Trinh, and T. H. Ngo, "Pedagogical design patterns in educational mobile apps: A comparative analysis of learning effectiveness across K–12, higher education, and professional training," *Journal of Interactive Mobile Technologies*, vol. 19, no. 22, pp. 4–21, 2025. <https://doi.org/10.3991/ijim.v19i22.58511>
- [18] Y. B. Limbu and L. Pham, "Impact of e-learning service quality on student satisfaction during the COVID-19 pandemic: A systematic review," *Knowledge Management & E-Learning*, vol. 15, no. 4, pp. 523–538, 2023. <https://doi.org/10.34105/j.kmel.2023.15.030>
- [19] N. Shehzad and T. Charles, "Exploring the impact of instructor social presence on student engagement in online higher education," *Contemporary Educational Technology*, vol. 15, no. 4, p. ep484, 2023. <https://doi.org/10.30935/cedtech/13823>
- [20] C. Cabi and H. Türkoglu, "The impact of a learning analytics-based feedback system on students' academic achievement and self-regulated learning in a flipped classroom," *International Review of Research in Open and Distributed Learning*, vol. 26, no. 1, pp. 175–196, 2025. <https://doi.org/10.19173/irrodl.v26i1.7924>
- [21] L. Cabral, R. Pinto, and G. Gonçalves, "AI-powered learning analytics dashboards: A systematic review of applications, techniques, and research gaps," *Discovery Education*, vol. 4, no. 525, pp. 1–27, 2025. <https://doi.org/10.1007/s44217-025-00964-y>
- [22] Q. Xia, W. Li, Y. Yang, X. Weng, and T. Chiu, "A systematic review and meta-analysis of the effectiveness of Generative Artificial Intelligence (GenAI) on students' motivation and engagement," *Computers and Education: Artificial Intelligence*, vol. 9, no. 100455, pp. 1–16, 2025. <https://doi.org/10.1016/j.caeai.2025.100455>
- [23] S. Hijazi, M. N. Mokal, A. Halder, V. Victor, and G. John, "AI- and IoT-driven mobile learning environments: A framework for educational transformation, workforce development, and digital inclusion," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 24, pp. 4–17, 2025. <https://doi.org/10.3991/ijim.v19i24.58959>
- [24] A. M. Al-Zahrani and T. M. Alasmari, "Exploring the impact of artificial intelligence on higher education: The dynamics of ethical, social, and educational implications," *Humanities and Social Sciences Communications*, vol. 11, no. 912, pp. 1–12, 2024. <https://doi.org/10.1057/s41599-024-03432-4>
- [25] C. Merino-Campos, "The impact of artificial intelligence on personalized learning in higher education: A systematic review," *Trends in Higher Education*, vol. 4, no. 17, pp. 1–15, 2025. <https://doi.org/10.3390/higheredu4020017>
- [26] S. V. Bentley, C. K. Naughtin, M. J. McGrath, J. L. Irons, and P. S. Cooper, "The digital divide in action: How experiences of digital technology shape future relationships with artificial intelligence," *AI and Ethics*, vol. 4, pp. 901–915, 2024. <https://doi.org/10.1007/s43681-024-00452-3>
- [27] Y. Walter, "Embracing the future of artificial intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education," *International Journal of Educational Technology in Higher Education*, vol. 21, no. 15, pp. 1–29, 2024. <https://doi.org/10.1186/s41239-024-00448-3>

- [28] H. Y. Ahn, “AI-powered e-learning for lifelong learners: Impact on performance and knowledge application,” *Sustainability*, vol. 16, no. 20, p. 9066, 2024. <https://doi.org/10.3390/su16209066>
- [29] A. Fortuna *et al.*, “Artificial intelligence in personalized learning: A global systematic review of current advancements and shaping future opportunities,” *Social Sciences & Humanities Open*, vol. 12, no. 102114, pp. 1–17, 2025. <https://doi.org/10.1016/j.ssaho.2025.102114>
- [30] U. Lah, J. R. Lewis, and B. Šumak, “Perceived usability and the modified technology acceptance model,” *International Journal of Human–Computer Interaction*, vol. 36, no. 13, p. 4811, 2020. <https://doi.org/10.1080/10447318.2020.1727262>
- [31] D. Al-Fraihat, M. Joy, R. Masa’deh, and J. Sinclair, “Evaluating E-learning systems success: An empirical study,” *Computers in Human Behavior*, vol. 102, pp. 67–86, 2020. <https://doi.org/10.1016/j.chb.2019.08.004>
- [32] D. Y. Long, S. Wang, S. M. Rashid, and X. T. Lu, “Artificial intelligence in higher education: A systematic review of its impact on student engagement and the mediating role of teaching methods,” *Frontiers in Education*, vol. 10, pp. 1–18, 2025. <https://doi.org/10.3389/educ.2025.1648661>
- [33] O. M. Chamorro *et al.*, “Microlearning and nanolearning in higher education: A bibliometric review to identify thematic prevalence in the COVID-19 pandemic and post-pandemic context,” *International Journal of Learning Teaching and Educational Research*, vol. 23, no. 4, pp. 279–297, 2024. <https://doi.org/10.26803/ijlter.23.4.15>
- [34] S. Kruger and A. A. Steyn, “Navigating the fourth industrial revolution: A systematic review of technology adoption model trends,” *Journal of Science and Technology Policy Management*, vol. 16, no. 10, pp. 24–56, 2025. <https://doi.org/10.1108/JSTPM-11-2022-0188>
- [35] S. Papadakis *et al.*, “Embracing digital innovation and cloud technologies for transformative learning experiences,” in *Proceedings of the 11th Workshop on Cloud Technologies in Education, CEUR Workshop Proceedings*, vol. 3679, 2024, pp. 1–21. [Online]. Available: <https://ceur-ws.org/Vol-3679/paper00.pdf>

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