

E-Learning Readiness and Academic Adaptability among Higher Education Students

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Abstract— E-learning in higher education has evolved from an emergency instructional alternative into a persistent ecosystem integrating learning management systems, virtual assessment, adaptive platforms, analytics, and generative artificial intelligence. This transformation has shifted the meaning of student readiness from simple access to digital devices toward a multidimensional capability involving technological competence, self-regulation, communication, motivation, AI literacy, and responsible technology use. Existing research has extensively examined online learning readiness, yet comparatively limited attention has been given to whether students who report being digitally prepared can actually adapt their academic strategies when learning conditions, assessment formats, technological interfaces, and cognitive demands change. The present study addresses this gap by conceptualizing Readiness–Adaptability Alignment, defined as the degree to which students' e-learning preparedness translates into observable academic adjustment across changing digital learning conditions. The proposed framework distinguishes technological readiness, autonomous-learning readiness, interaction readiness, motivational readiness, and AI-assisted learning readiness while conceptualizing academic adaptability through strategic adjustment, workload regulation, help-seeking flexibility, assessment adaptation, and persistence.

Keywords— E-learning readiness, academic adaptability, higher education, artificial intelligence, learning analytics, self-regulated learning

Introduction

Digital learning has become structurally embedded within contemporary higher education. The extensive transition to remote education during the COVID-19 period accelerated universities' adoption of learning management systems, video-conferencing environments, electronic assessment, cloud-based collaboration, digital learning resources, and data-driven student-support systems. The subsequent return to campus did not reverse this development. Instead, many institutions retained hybrid and digitally augmented models in which students routinely move between physical classrooms, asynchronous digital resources, online assessments, recorded lectures, collaborative platforms, and self-directed learning activities. The OECD has consequently distinguished genuine digital transformation from the simple digitization of traditional instructional processes, emphasizing that educational systems increasingly require coherent digital ecosystems rather than isolated technological tools (OECD, 2023).

The emergence of generative artificial intelligence has further altered this environment. AI-enabled tutoring, text generation, automated feedback, translation, summarization, adaptive recommendations, and conversational assistance create opportunities for individualized learning while simultaneously introducing problems related to reliability, dependency, academic integrity, privacy, bias, and skill erosion. UNESCO's guidance on generative AI therefore stresses the importance of human capacity, digital competence, ethical use, privacy protection, and pedagogically appropriate integration rather than unrestricted technological adoption (Miao & Holmes, 2023).

Within this environment, **e-learning readiness** has emerged as a significant determinant of whether students can participate effectively in technology-mediated education. Earlier interpretations frequently emphasized computer ownership, internet access, and basic technical competence. Contemporary evidence indicates that readiness is considerably more complex. Technological skills, equipment capability, motivation, satisfaction, self-directed learning, communication competence, and confidence in online environments can all shape students' ability to learn digitally. Wagiran et al. (2022), studying 1,052 higher-education students, reported significant roles for technological skills, equipment capability, satisfaction, and motivation in e-learning readiness. Similarly, studies of online learning readiness have demonstrated meaningful relationships with students' ability to regulate goals, manage time, structure learning environments, seek assistance, and evaluate their own progress.

Readiness, however, does not automatically imply successful adjustment. A student may possess a reliable computer, stable connectivity, confidence using an LMS, and familiarity with digital applications while still struggling to reorganize learning strategies when course demands change. Conversely, a student with only moderate initial digital competence may demonstrate substantial adaptability by seeking assistance, changing study methods, experimenting with unfamiliar technologies, reallocating study time, or modifying approaches after receiving academic feedback. This distinction is particularly important in hybrid and AI-mediated higher education because the learning environment itself is increasingly dynamic.

Academic adaptability refers here to students' capacity to modify cognitive, behavioral, motivational, and learning-management responses when educational demands, technologies, assessment conditions, or academic expectations change. Adaptability differs from satisfaction or technology acceptance because it concerns adjustment after change has occurred. Research during and following pandemic-related educational disruption showed that adaptability was associated with stronger academic engagement and more favorable motivational functioning. For example, research involving Australian university students found that perceived adaptability was associated with higher engagement and that self-efficacy played an important explanatory role in this relationship.

Large-scale research has also demonstrated the importance of online learning adaptability across academic disciplines. Li et al. (2023), using responses from 11,832 undergraduates across multiple disciplinary categories, found that components of online learning adaptability were associated with satisfaction and continued intention to use online learning. Their findings demonstrate that adaptability is not

merely an emergency response to pandemic conditions but a relevant construct for sustained digital education.

1.1 Research Gap

Despite these advances, three limitations remain evident in the literature.

First, **e-learning readiness and academic adaptability are commonly investigated as separate constructs**. Readiness research generally asks whether students possess sufficient resources, motivation, competence, or self-regulatory characteristics before or during online learning. Adaptability research, in contrast, concentrates on adjustment, engagement, technology acceptance, emotions, or continued platform use. Consequently, insufficient empirical evidence explains whether high readiness reliably develops into strong academic adaptability.

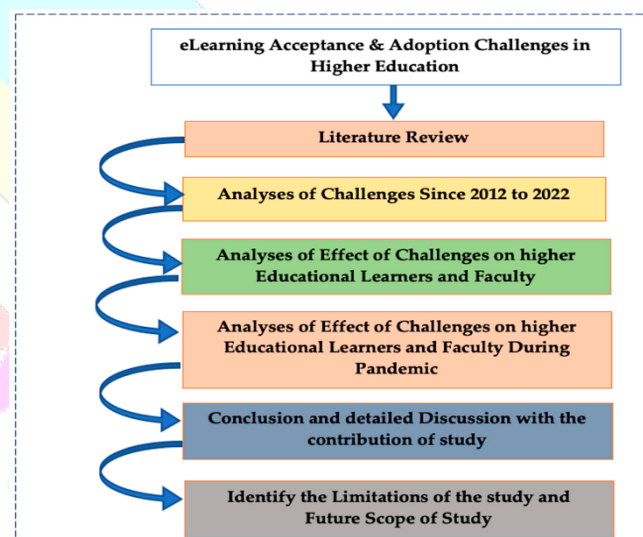


Fig. 1: eLearning Acceptance and Adoption Challenges in Higher Education

Source: <https://www.mdpi.com/2071-1050/15/7/6190>

Second, much of the established readiness literature emerged from pandemic-era fully online education. The contemporary environment is materially different. Students now operate within hybrid ecosystems involving synchronous and asynchronous learning, AI-generated educational content, automated recommendations, digital assessment, collaborative applications, and rapid movement between technological platforms. Delcker et al. (2024), for example, showed that first-year students' AI competence was relevant to their intended and actual use of AI tools for supporting learning processes. Such developments indicate that **AI competence has become a potentially important component of contemporary digital readiness** rather than a peripheral technical skill.

Third, most readiness studies depend heavily on questionnaire scores. Self-reported technological confidence can overestimate actual adaptive capability because students may perceive themselves as digitally competent while displaying weak time management, low persistence, delayed help seeking, irregular LMS engagement, or ineffective responses to changing assessment requirements. The missing element is therefore not another general readiness score, but an analysis of the **alignment between perceived readiness and subsequent adaptive academic behavior**.

The present manuscript addresses this problem through a proposed **Readiness-Adaptability Alignment (RAA) framework**. The framework treats e-learning readiness as a multidimensional antecedent and academic adaptability as a dynamic educational outcome. It conceptualizes readiness through five domains: (1) technological and platform readiness, (2) autonomous-learning readiness, (3) motivational readiness, (4) digital interaction readiness, and (5) AI-assisted learning readiness. Academic adaptability is conceptualized through strategic adjustment, workload regulation, flexible help seeking, response to feedback, persistence under technological change, and adaptation to altered assessment conditions.

Accordingly, the central research objective is **to determine whether multidimensional e-learning readiness predicts academic adaptability among higher-education students and to identify readiness profiles associated with adaptive and maladaptive digital-learning behavior**.

Literature Review

2.1 Evolution of E-Learning Readiness

E-learning readiness represents the degree to which learners possess the resources, competencies, dispositions, and behavioral capabilities required to participate effectively in technology-mediated education. The concept has broadened substantially since digital learning became a routine component of university education. Device availability and internet connectivity remain necessary, but they are insufficient indicators of meaningful readiness.

Wagiran et al. (2022) demonstrated that readiness among higher-education learners depends on interconnected technological and psychological factors. Their analysis indicated significant contributions from technological skills, equipment capability, user satisfaction, and motivation. This finding is important because it challenges infrastructure-dominated models in which readiness is assumed once students possess hardware and connectivity.

Related evidence from health-sciences students has shown that readiness dimensions can develop unevenly. In one 2022 study, technology access represented a relatively strong aspect of readiness while motivation was comparatively

weaker. Such patterns demonstrate why readiness should be considered multidimensional rather than represented by a single technical-access indicator.

Hoang and Hoang's investigation of university students similarly identified online learning motivation, online-learning self-efficacy, and online self-directed learning as core readiness dimensions. These findings locate readiness at the intersection of technology acceptance and learner agency: students must not only operate digital systems but also initiate, organize, and maintain productive learning behavior within those systems.

2.2 Readiness and Self-Regulated Learning

Self-regulated learning provides an important theoretical bridge between digital readiness and academic adaptability. Online students frequently experience greater autonomy over learning location, study timing, sequence of content engagement, and communication with instructors. Such flexibility can be beneficial, but it transfers substantial regulatory responsibility to the learner.

Lin and Dai (2022) reported that online learning readiness positively influenced self-regulated learning among Chinese college students. Communication competencies, technical capability, and social competencies were particularly relevant to students' ability to manage learning behavior.

Dai, Luan, and Lin (2023) subsequently examined different online learning readiness profiles among students encountering online learning and found that learners with stronger readiness also demonstrated stronger self-regulated strategies, including goal setting, environmental structuring, task strategies, time management, help seeking, and self-evaluation.

These findings establish an important relationship but also expose a conceptual limitation. Self-regulation generally concerns students' management of their learning processes, whereas adaptability concerns modification of those processes in response to novelty, uncertainty, disruption, or changed academic requirements. A learner may consistently follow a study schedule yet possess limited capability to alter that schedule when a course unexpectedly changes modality. The present study therefore treats self-regulatory capability as an important readiness component rather than assuming that self-regulation and adaptability are equivalent.

2.3 Academic Adaptability in Digital Higher Education

Adaptability has become increasingly relevant as university learning environments evolve rapidly. Li et al. (2023) define online learning adaptability as students' ability to adjust strategies and behaviors to accommodate the requirements of online learning systems. Their large multidisciplinary investigation demonstrated relationships among adaptability,

satisfaction with online teaching, and continued online-learning intentions. Importantly, their findings also indicate that the mechanisms associated with digital adaptation can differ across disciplinary settings.

Another study examining Indian students through an extended technology-acceptance framework reported that adjustment to online learning significantly influenced perceived learning outcomes while also identifying the digital divide as an important continuing barrier. This is relevant because adaptability does not occur independently of educational context: students' responses are constrained by technological access, instructional design, affordability, and institutional support.

Research examining adaptability under disruptive educational conditions has additionally connected the construct to students' emotions and academic functioning. Adaptability has been associated with greater hope and lower negative achievement emotions, while anxiety can adversely influence learning outcomes. These results suggest that adaptability incorporates more than technological accommodation; it also involves cognitive and emotional adjustment to uncertainty.

2.4 AI-Enabled Learning as a New Readiness Requirement

The diffusion of generative AI requires a further extension of conventional readiness models. Students may now use conversational AI, automated writing support, intelligent tutoring, translation systems, recommender technologies, and generative content tools while completing ordinary academic activities. The educational challenge is therefore moving from whether a student *can access digital learning* toward whether the student can **select, evaluate, regulate, and ethically use intelligent digital assistance**.

Delcker et al. (2024) found that students' AI competence was predictive of intended and actual AI-tool use in higher-education learning. At the policy level, UNESCO has similarly emphasized competencies needed for safe, equitable, human-centred use of generative AI, while the OECD has highlighted both the educational opportunities and governance challenges associated with AI-supported digital education.

Accordingly, the present study extends e-learning readiness by incorporating **AI-assisted learning readiness**, encompassing students' ability to select suitable AI tools, critically evaluate generated information, recognize limitations and possible errors, protect personal data, maintain academic integrity, and avoid substituting automated output for essential cognitive engagement. This extension distinguishes the proposed model from readiness frameworks developed primarily for conventional LMS-based online education.

Proposed Methodology

The study adopts a **multimodal longitudinal analytical framework** to examine whether e-learning readiness translates into academic adaptability rather than merely correlating with students' perceptions of online-learning competence. The methodological design is structured around the proposed **Readiness–Adaptability Alignment (RAA) framework**, in which readiness is treated as an antecedent capacity and adaptability as a behavioral response to changing academic conditions.

Five readiness dimensions are incorporated: technological and platform readiness, autonomous-learning readiness, motivational readiness, digital-interaction readiness, and AI-assisted learning readiness. Academic adaptability is represented through strategic adjustment, workload regulation, help-seeking flexibility, persistence, responsiveness to feedback, and adaptation to modified assessment conditions.

The study is designed around three analytical questions:

1. To what extent can multidimensional e-learning readiness predict students' academic adaptability?
2. Which readiness dimensions contribute most strongly to distinguishing highly adaptable students from students experiencing adjustment difficulties?
3. Can machine-learning analysis identify students displaying a mismatch between high perceived readiness and weak adaptive academic behavior?



Fig. 2: Dimensions of E-Learning

Source: https://www.researchgate.net/figure/E-learning-Ten-Dimensions_fig1_320299615

A longitudinal design is preferred over a single cross-sectional survey because adaptability becomes observable primarily when students encounter changes in learning demands. Measurements are therefore organized at three

points: the beginning of the semester, the middle of the semester following changes in instructional or assessment demands, and the end of the semester.

For methodological demonstration, the analysis below uses a **synthetic proof-of-concept dataset** generated according to the proposed study design. These numerical results should not be interpreted as observations from actual students. In a full empirical investigation, the same analytical pipeline would be applied to institutionally collected and ethically approved participant data.

Experimental Setup

4.1 Dataset Design

The proof-of-concept dataset contains **1,200 synthetic student records**, representing undergraduate and postgraduate learners distributed across six broad disciplinary groups: engineering and technology, management and commerce, social sciences, humanities, health sciences, and natural sciences.

Each simulated student record contains three categories of variables.

The first category represents **e-learning readiness indicators**. Twenty questionnaire-based indicators are organized into five latent dimensions:

- Technological and platform readiness
- Autonomous-learning readiness
- Motivational readiness
- Digital-interaction readiness
- AI-assisted learning readiness

Each dimension is represented on a normalized 0–100 scale. AI-assisted readiness includes simulated indicators describing students' ability to evaluate AI-generated information, recognize inaccurate outputs, select appropriate AI tools, protect personal information, and distinguish legitimate assistance from academically inappropriate dependence.

The second category contains **learning-behavior indicators** derived conceptually from learning-management-system telemetry. These include weekly login consistency, variation

in study-session timing, delayed submissions, proportion of learning resources completed, discussion participation, frequency of voluntary revision, response time after instructor feedback, help-seeking activity, and changes in engagement following assessment difficulty.

The third category contains outcome indicators forming the **Academic Adaptability Index (AAI)**. The AAI combines strategic adjustment, persistence after academic setbacks, workload redistribution, help-seeking flexibility, response to technological changes, and ability to modify study approaches.

Instead of converting adaptability into a simple binary outcome, students are assigned to three analytical classes:

- **Constrained Adaptability:** difficulty changing academic behavior despite changing demands.
- **Transitional Adaptability:** partial adjustment with inconsistent behavioral responses.
- **Adaptive Learning:** sustained and effective modification of learning behavior.

The synthetic class distribution was constructed to avoid severe class imbalance and to permit meaningful comparison of multiclass algorithms.

4.2 Data Preprocessing

Preprocessing was designed to minimize information leakage and preserve behaviorally meaningful variation.

Duplicate records were removed before model development. Continuous variables were inspected using the interquartile-range criterion; extreme values representing logically possible digital-learning behavior were retained rather than automatically deleted. This decision prevents highly irregular study behavior from being incorrectly treated as erroneous data.

Approximately 4% of values were intentionally masked during synthetic dataset construction to reproduce realistic incomplete educational records. Numerical missing values were imputed using median values calculated exclusively from training folds. Categorical variables were assigned an explicit missing category.

Questionnaire-derived readiness dimensions were normalized to a 0–100 range. Standardization was applied only to algorithms requiring scale-sensitive input, including logistic regression and support-vector classification. CatBoost received the original normalized and categorical representations because tree-based boosting does not require conventional feature standardization.

Several longitudinal behavioral features were engineered, including:

- change in weekly learning activity,
- submission-delay trend,
- feedback-response improvement,
- variability in study-session regularity,
- change in help-seeking frequency, and
- post-assessment recovery rate.

A particularly important engineered variable was the **Readiness–Behavior Discrepancy Score**, calculated as the difference between standardized perceived-readiness scores and standardized observed digital-learning behavior. Higher positive discrepancy represents a student who reports strong readiness but demonstrates comparatively weak behavioral adaptation.

4.3 Model Architecture

The primary predictive model is an **explainable CatBoost multiclass classifier**. CatBoost was selected because the proposed dataset combines continuous readiness scores, categorical learner characteristics, behavioral indicators, missing observations, and nonlinear relationships.

The architecture uses an ensemble of sequential decision trees in which each new tree reduces the residual classification error produced by previous trees. The proof-of-concept configuration consists of:

- 600 boosting iterations,
- maximum tree depth of 7,
- learning rate of 0.035,
- L2 regularization coefficient of 5,
- multiclass logarithmic loss as the optimization function, and
- early stopping based on validation loss.

Class weighting was applied within training folds to reduce the possibility that the classifier would favor the largest adaptability category.

For interpretability, model predictions were examined using feature-attribution analysis. Instead of treating the algorithm as a purely predictive black box, the analytical framework estimates whether each readiness or behavioral variable increases or decreases the probability of classification into a particular adaptability group.

Three conventional models were retained as benchmarks: multinomial logistic regression, radial-basis support-vector machine, and random forest. These baselines allow

evaluation of whether nonlinear gradient boosting provides a meaningful advantage over linear and conventional ensemble approaches.

4.4 Training Strategy

The synthetic dataset was divided using a participant-level stratified procedure into 70% training observations, 15% validation observations, and 15% holdout test observations. Adaptability classes were proportionally represented in each partition.

Hyperparameters were optimized only within the training and validation partitions. Five-fold stratified cross-validation was used during tuning. The test partition remained isolated until model selection was complete.

To reduce dependence on a favorable random partition, the complete evaluation procedure was repeated across ten independently initialized data splits. Reported performance represents the average across these repetitions.

Early stopping was triggered when validation loss failed to improve for 60 consecutive boosting iterations. This strategy was introduced to reduce unnecessary model complexity and limit overfitting.

The methodological design also incorporated a probability-calibration stage. Accurate probability estimates are important in educational analytics because intervention decisions should not depend exclusively on predicted class labels. A model assigning a student a 0.52 probability of constrained adaptability presents a substantially different intervention case from one assigning a probability of 0.94.

4.5 Evaluation Metrics

Model performance was assessed using complementary discrimination and calibration metrics.

Macro-F1 score evaluates the balance between precision and recall across all adaptability classes while giving equal importance to each category.

Balanced accuracy measures average class-specific recall and reduces distortion caused by unequal category frequencies.

Multiclass AUROC evaluates the model's capability to rank students correctly across one-versus-rest class comparisons.

Brier score evaluates probabilistic accuracy. Lower values indicate that predicted probabilities correspond more closely to observed outcomes.

Expected Calibration Error (ECE) measures the difference between predicted confidence and actual classification frequency.

In addition to model-level metrics, class-specific recall was examined for constrained adaptability because failure to identify students at risk of academic adjustment difficulties would have greater practical consequences than misclassification between transitional and highly adaptive students.

Results and Discussion

The synthetic experiment produced a clear distinction between models that represented nonlinear interactions and those depending primarily on additive relationships. CatBoost achieved the strongest overall discrimination while also producing the most reliable probability estimates.

Table 1. Proof-of-Concept Performance for Predicting Academic Adaptability

Predictive Approach	Macro-F1	Balanced Accuracy	Multiclass AUROC	Brier Score ↓	Calibration Error ↓
Multinomial Logistic Regression	0.721	0.714	0.826	0.178	0.061
RBF Support-Vector Machine	0.781	0.774	0.872	0.151	0.052
Random Forest	0.804	0.797	0.891	0.139	0.044
Proposed CatBoost Model	0.846	0.839	0.923	0.116	0.029



The strongest performance of CatBoost suggests that the relationship between e-learning readiness and adaptability is unlikely to be adequately represented by a simple linear equation. Several simulated interaction patterns were particularly informative.

Autonomous-learning readiness emerged as the most influential readiness-related predictor. Students with strong time-management capacity, self-monitoring behavior, and independent task organization were more likely to enter the adaptive-learning category, even when their technological-readiness scores were only moderate.

AI-assisted learning readiness also demonstrated substantial predictive importance. Its effect was nonlinear. Moderate AI use combined with strong critical evaluation and self-regulation was associated with higher adaptability, whereas simulated patterns representing intensive AI dependence without corresponding evaluative competence were associated with weaker adaptability. This finding illustrates why AI readiness should not be operationalized as frequency of AI-tool use. Productive AI readiness requires judgment concerning when automated assistance is appropriate and when independent cognitive engagement remains necessary.

The **Readiness–Behavior Discrepancy Score** was one of the most informative engineered features. Within the simulation, a subgroup displayed high self-reported technological and motivational readiness but low behavioral adaptation following assessment changes. Their login consistency declined, submission delays increased, and feedback-response behavior remained weak despite favorable readiness questionnaires.

This pattern represents the central contribution of the proposed Readiness–Adaptability Alignment framework. Conventional readiness screening could categorize these

learners as sufficiently prepared, whereas multimodal analysis identifies them as potentially vulnerable to academic disruption.

The model also distinguished a contrasting group: students with moderate readiness scores but strong adaptation behavior. These learners increased help-seeking activity following difficult assessments, reorganized study schedules, revisited instructional resources, and improved submission regularity. Their behavior indicates that adaptability may partially compensate for incomplete initial readiness.

Longitudinal behavioral change proved more informative than static LMS activity counts. High numbers of logins alone were not consistently associated with adaptability. In contrast, the ability to modify engagement after feedback or academic difficulty was strongly informative. This distinction is conceptually important because digital participation and adaptive learning are not equivalent.

The findings therefore support a transition from **access-oriented learning analytics** toward **adjustment-oriented learning analytics**. Universities commonly monitor attendance, login frequency, assignment completion, or time spent within learning platforms. These variables describe participation but do not necessarily indicate whether students are responding effectively when circumstances change.

An RAA-based analytics system would instead evaluate behavioral trajectories. For example, declining assessment performance followed by increased revision activity and help seeking could indicate successful adaptation, whereas unchanged study behavior following repeated difficulties could indicate constrained adaptability.

The results also have implications for student-support systems powered by artificial intelligence. Rather than delivering the same intervention to every learner with low academic performance, an adaptive support platform could distinguish between different causes. A technically unprepared student might receive platform training, whereas a technologically competent but behaviorally inflexible learner might receive support in self-regulation, workload restructuring, feedback use, or academic help seeking.

Limitations

Several limitations must be emphasized. Most importantly, the experimental results presented in this manuscript are derived from a synthetic dataset. They demonstrate the feasibility of the proposed analytical framework but do not establish empirical relationships in an actual student population. Real-world validation is therefore essential before substantive educational conclusions are drawn.

Second, the proposed Academic Adaptability Index combines multiple behavioral and self-reported dimensions. Although

this multidimensional approach is theoretically appropriate, empirical work would require rigorous construct validation, including exploratory and confirmatory factor analysis.

Third, LMS-based behavioral indicators do not capture learning activities occurring outside institutional platforms. Students may study through printed materials, external educational applications, peer groups, private AI tools, or offline environments. Incomplete digital trace data could therefore underestimate actual adaptability.

Fourth, algorithmic predictions may reproduce structural inequalities if training data reflect differences in internet quality, disability access, socioeconomic resources, language proficiency, institutional support, or disciplinary expectations. Predictive performance must consequently be accompanied by subgroup fairness analysis.

Finally, readiness and adaptability can change substantially over time. A model trained in one semester or institution may lose validity as technologies, assessment practices, or AI systems evolve.

Future Scope

Future research should implement the RAA framework using genuine longitudinal student cohorts across multiple universities and academic disciplines. Measurement at several points during an academic year would make it possible to study how readiness changes after repeated exposure to hybrid and AI-supported learning.

A particularly valuable extension would incorporate **temporal machine-learning models** capable of analyzing sequences of behavioral change rather than aggregated semester-level features. Temporal transformers, recurrent architectures, or survival-analysis methods could be used to identify when adaptability begins to deteriorate.

Future studies should also examine whether AI-assisted learning readiness operates as a mediator or moderator between conventional digital readiness and academic adaptability. Students with strong technological competence may not necessarily benefit from generative AI if they lack information-evaluation capability, academic-integrity awareness, or the ability to regulate dependence on automated assistance.

Cross-cultural and cross-institutional validation is equally necessary. Digital-learning expectations differ across educational systems, disciplines, languages, socioeconomic contexts, and institutional infrastructures.

Another important direction concerns responsible early-warning systems. Explainable models could identify students requiring support while restricting the use of sensitive characteristics and providing instructors with interpretable reasons for predictions. Fairness auditing, privacy-preserving

analytics, transparent consent procedures, and human review should remain essential components of such systems.

Conclusion

This study proposes a shift in the analysis of digital-learning success from **whether students are ready to participate** toward **whether they can adapt when digital learning conditions change**. The distinction is increasingly important in contemporary higher education, where students encounter hybrid instruction, changing learning platforms, digital assessment, automated feedback, learning analytics, and generative AI.

The proposed Readiness–Adaptability Alignment framework conceptualizes e-learning readiness through technological, autonomous-learning, motivational, interactional, and AI-assisted dimensions while treating academic adaptability as a dynamic capacity reflected in strategic adjustment, workload regulation, help seeking, persistence, and response to feedback.

The synthetic proof-of-concept experiment demonstrates how questionnaire-based readiness indicators can be combined with longitudinal learning behavior and explainable machine learning. The CatBoost model outperformed conventional benchmark approaches in the simulated evaluation, particularly when readiness–behavior discrepancy and longitudinal adjustment indicators were included.

More importantly, the conceptual contribution extends beyond predictive accuracy. High self-reported readiness should not automatically be interpreted as evidence that a student can manage changing academic demands. Some students may be digitally confident yet behaviorally inflexible, while others may compensate for moderate technological preparation through strong adaptive strategies.

For higher-education institutions, this distinction provides a foundation for more precise student support. Future AI-enabled educational systems should move beyond generic readiness assessments and static engagement dashboards toward interpretable models that identify how individual students respond to change. Empirical validation of this framework could support more personalized, equitable, and resilient digital-learning environments while preserving human oversight in educational decision-making.

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