



Educational Technology and Personalized Learning Experiences among College Students

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<http://www.gjirp.org/> || Vol. 2 No. 3 (2026): Special August Issue

Date of Submission: 15-07-2026

Date of Acceptance: 31-07-2026

Date of Publication: 20-08-2026

Abstract: Educational technology is increasingly shifting higher education from uniform digital instruction toward data-informed and individually adaptive learning environments.

This study examines how AI-enabled educational technologies influence personalized learning experiences, academic engagement, and self-regulated learning among college students with differing levels of digital readiness. A specific research gap is identified in the limited integration of learner heterogeneity, behavioral interaction data, and perceived personalization within a single analytical framework. The proposed research conceptualizes personalization as a multidimensional process involving adaptive content sequencing, individualized feedback, learning-resource recommendations, and learner-controlled pacing rather than simple technology exposure. Student interaction traces and questionnaire-based indicators are proposed for constructing learner profiles representing academic behavior, technological readiness, engagement, and self-regulation. A hybrid machine-learning framework is designed to identify learner profiles and predict the degree to which students benefit from personalized educational interventions.

The study further investigates whether perceived personalization mediates the relationship between educational technology use and meaningful learning engagement.

The anticipated contribution is a student-centered framework for evaluating when, for whom, and under

what technological conditions personalized learning produces beneficial higher-education experiences.

Keywords: Educational Technology; Personalized Learning; Artificial Intelligence in Education; Learning Analytics; Self-Regulated Learning; College Students

1. Introduction

Higher education has entered a phase in which digital technology is no longer used solely to distribute instructional materials. Contemporary learning environments increasingly include learning management systems, intelligent tutoring tools, adaptive assessment platforms, recommendation engines, learning analytics dashboards, conversational artificial intelligence, and automated feedback applications. Collectively, these technologies are changing the informational structure of teaching and learning. Rather than presenting identical resources and instructional sequences to an entire class, technologically mediated systems can potentially respond to differences in prior knowledge, learning pace, patterns of participation, performance, and educational needs. The resulting movement toward personalized learning represents one of the most consequential developments in digitally mediated higher education.

Personalized learning may be understood as the systematic adaptation of instructional content, learning pathways, feedback, pacing, or support according to characteristics of an individual learner. The OECD emphasizes personalization as an important potential benefit of digital education,





particularly where digital systems can identify learner-specific information, diagnose learning needs, and recommend appropriate interventions. Artificial intelligence further extends this capacity by enabling educational systems to process relatively complex combinations of behavioral, performance, and interaction data when generating learning recommendations (OECD, 2023).

The relevance of personalization has become particularly pronounced within colleges and universities. Student populations are heterogeneous in academic preparation, socioeconomic background, technological competence, disciplinary knowledge, language proficiency, motivation, learning preferences, and capacity for independent study. Conventional teaching models generally accommodate this diversity through instructor judgment and differentiated support, but institutional scale frequently restricts the degree of individualization that instructors can provide. Educational technology therefore offers a potentially scalable mechanism for complementing instructor-led personalization.

Technological personalization, however, should not be equated with the mere availability of digital content. A student who accesses a learning management system containing recorded lectures and electronic documents is receiving digitally delivered education, but not necessarily personalized education. Genuine personalization requires some form of learner-sensitive adaptation. This adaptation may involve recommending remedial material following an incorrect response, adjusting task difficulty, providing alternative explanations, changing the sequence of instructional activities, generating individualized formative feedback, or enabling students to follow learning paths suited to their demonstrated competencies.

Recent evidence supports the potential value of such approaches while also indicating substantial variability in their effectiveness. A 2024 scoping review of personalized adaptive learning in higher education reported positive effects on academic performance in a majority of the reviewed studies, although improvements in student engagement appeared in a smaller proportion. The review also identified limitations associated with technology infrastructure, implementation time, and differences in how adaptive learning was operationalized across studies. These findings indicate that the educational value of personalization cannot be adequately represented through a simple technological-versus-nontechnological comparison.

This issue has become more complex following the rapid diffusion of generative AI. Contemporary students can interact with AI systems that generate explanations, practice questions, summaries, examples, feedback, translations, and study assistance almost instantaneously. Such systems introduce a considerably more dynamic form of

personalization than traditional preprogrammed adaptive platforms. At the same time, the increased autonomy of AI systems introduces concerns regarding accuracy, privacy, algorithmic bias, learner dependence, transparency, and appropriate human oversight. UNESCO's guidance on generative AI consequently stresses that educational adoption should remain human-centered and should incorporate ethical validation, privacy protection, pedagogical appropriateness, and responsible institutional governance (Miao & Holmes, 2023).

These developments reveal an important distinction between **technology use** and **personalized learning experience**. Two college students may use the same educational platform for an identical amount of time yet experience very different educational benefits. A student with strong self-regulation and high digital readiness may effectively interpret recommendations and select appropriate learning activities. Another learner may receive technically personalized resources but fail to translate those recommendations into meaningful learning actions. Personalization is therefore simultaneously a property of a technological system and an experience produced through interaction between the learner and that system.

Research Gap

Existing higher-education research has extensively investigated technology acceptance, online-learning satisfaction, adaptive learning systems, academic achievement, and student engagement. Systematic reviews have also documented substantial growth in research concerning personalized learning and AI-supported adaptation. Fariani, Junus, and Santoso (2023), for example, demonstrated that personalized learning research incorporates diverse learner characteristics, personalization features, technological approaches, and theoretical foundations. More recent reviews have similarly highlighted AI-driven adaptive systems and automated personalization.

Nevertheless, three related limitations remain evident. First, many studies assess educational technology according to platform-level outcomes such as grades, completion, satisfaction, or general engagement rather than distinguishing the specific mechanisms through which students experience personalization. Second, learner characteristics such as digital readiness, prior academic competence, self-regulation, and behavioral participation are frequently examined separately rather than as interacting sources of learner heterogeneity. Third, relatively little research simultaneously combines students' subjective perceptions of personalization with objective digital-learning behavior to determine why identical personalization mechanisms may produce different outcomes across students.





The present study addresses this gap by conceptualizing personalized learning as an interaction between **adaptive technological affordances and learner-specific readiness**. Rather than asking whether educational technology improves learning in general, the research asks a more discriminating question: **Which combinations of learner characteristics and technology-mediated personalization are associated with stronger engagement and self-regulated learning among college students?**

Accordingly, the proposed study has four objectives: to evaluate students' experiences of adaptive content, individualized feedback, resource recommendation, and flexible learning pathways; to identify distinct student profiles using behavioral and digital-readiness indicators; to determine whether personalized learning experience predicts engagement and self-regulated learning after controlling for general technology usage; and to develop a machine-learning model capable of identifying students who may require additional human or technological support.

This approach positions artificial intelligence and machine learning not as replacements for conventional pedagogy but as analytical mechanisms through which heterogeneous learning behavior can be detected and educational support can be more precisely allocated. Such a perspective is consistent with emerging international recommendations emphasizing that digital transformation should increase educational effectiveness while maintaining appropriate human involvement, fairness, transparency, and learner agency.

2. Literature Review

2.1 Evolution of Educational Technology in Higher Education

Educational technology in universities has progressed from supplementary computer-assisted instruction toward integrated digital ecosystems. Learning management systems initially centralized course resources, assignments, assessments, communication, and grade reporting. Subsequent developments introduced learning analytics capable of transforming clickstreams, assessment records, submission patterns, and interaction histories into indicators of student progress.

The contemporary phase increasingly incorporates AI-based technologies capable of prediction and adaptation. Machine-learning algorithms can identify patterns across large quantities of learner data, while natural-language-processing systems can provide automated responses and analyze written interactions. Recommendation algorithms can prioritize learning resources, and intelligent tutoring systems can modify instruction following student responses. More recently, large language models have introduced

conversational interaction in which explanations and educational materials can be dynamically generated.

The significance of this progression lies in the movement from *digitization* toward *adaptive decision-making*. Digital education becomes genuinely personalized when information about a learner changes what that learner subsequently receives. OECD analysis similarly characterizes personalization as a process involving learner-specific information, diagnosis, recommendation, and intervention rather than simply presenting educational material electronically (OECD, 2023).

2.2 Personalized Learning as a Multidimensional Construct

Personalization has been operationalized differently across educational studies. Some systems focus on adaptive difficulty, whereas others personalize instructional sequences, recommendations, feedback, assessment, or pacing. Consequently, evaluating personalized learning solely according to the presence of an adaptive platform can obscure meaningful differences in students' actual experiences.

For the present study, personalized learning experience is conceptualized through four interconnected dimensions. **Adaptive content sequencing** represents the extent to which instructional material responds to a student's demonstrated knowledge. **Individualized feedback** captures whether students receive sufficiently specific information about misconceptions and improvement strategies. **Personalized resource recommendation** concerns the provision of learning activities or resources corresponding to identifiable learner needs. **Learner-controlled pacing and pathways** represent the extent to which technology permits students to regulate progression without eliminating essential instructional structure.

This multidimensional approach also recognizes that algorithmic adaptation and learner agency should not necessarily be treated as competing models. Highly automated personalization can become restrictive when students are unable to understand or override recommendations. Conversely, complete learner control may create difficulties for students lacking metacognitive or self-regulatory competence. Effective personalization may therefore require an appropriate balance between automated guidance and informed learner choice.

2.3 Artificial Intelligence and Adaptive Learning

Artificial intelligence has expanded the technical possibilities available for personalized instruction. AI-enabled adaptive systems can analyze response accuracy, error patterns, task duration, content interaction, and previous performance





before modifying subsequent learning activities. Recent systematic evidence indicates growing use of machine learning, natural-language processing, and hybrid AI techniques within adaptive higher-education environments.

However, the effectiveness of AI personalization depends on the educational quality of the underlying adaptation. An algorithm may successfully predict that a student is at risk without necessarily providing an intervention that improves learning. Similarly, a recommendation system may accurately identify relevant educational resources while presenting too many options for the learner to process efficiently.

This distinction suggests that prediction accuracy should not become the sole criterion for evaluating AI-supported education. Educationally meaningful evaluation requires consideration of whether recommendations support comprehension, learner autonomy, sustained participation, and effective study behavior. The present investigation consequently integrates machine-learning prediction with educational constructs instead of treating algorithmic performance as an independent end point.

2.4 Personalized Learning and Student Engagement

Student engagement is commonly represented through behavioral, cognitive, and emotional dimensions. Educational technology can influence each dimension differently. Personalized reminders and activity recommendations may increase behavioral participation; adaptive instructional challenges may stimulate cognitive engagement; and individualized feedback may enhance perceived relevance or competence.

Nevertheless, personalization does not automatically increase engagement. Excessive notifications, inappropriate recommendations, unstable adaptation, or insufficiently transparent algorithms may produce frustration rather than involvement. The 2024 scoping review of personalized adaptive learning found evidence of engagement improvement but also demonstrated that positive engagement effects were less consistently reported than academic-performance improvements.

This inconsistency indicates that engagement should be treated as an outcome requiring explanation rather than an assumed consequence of personalization. One plausible explanation is learner heterogeneity. Students differ in their willingness to follow automated recommendations, confidence in using digital tools, study discipline, and capacity to interpret performance feedback. The same intervention may therefore generate high engagement among one learner group while having negligible effects among another.

2.5 Self-Regulated Learning and Digital Readiness

Self-regulated learning refers broadly to learners' capacity to plan, monitor, control, and evaluate their learning processes. Personalized technologies frequently assume some degree of this capability. Even when an adaptive platform identifies appropriate instructional material, students may still need to allocate study time, maintain attention, interpret feedback, and decide when additional assistance is necessary.

Digital readiness adds another layer to this relationship. It extends beyond access to devices and includes competence, confidence, familiarity with digital environments, ability to evaluate digital information, and capacity to use technological features effectively. Students with similar academic ability may therefore respond differently to the same personalized interface.

The OECD notes that increasingly sophisticated personalization can consider not only what students need to learn but also dimensions such as motivation, effort, and self-regulation. This shift reinforces the need to model learner characteristics alongside academic-performance indicators when designing or evaluating personalized systems.

2.6 Generative AI and the New Personalization Environment

Generative AI has altered the scale and immediacy of personalized educational interaction. Unlike many earlier adaptive-learning platforms, generative systems can construct new explanations, quizzes, examples, summaries, and conversational responses at the point of use. Students can request simpler explanations, change the level of detail, ask follow-up questions, translate concepts, or generate practice materials according to individual needs.

These capabilities expand personalization but create methodological and ethical complexities. The educational interaction is no longer completely determined by institutional instructional design because students themselves can formulate prompts and modify the nature of the assistance received. Consequently, learning outcomes depend partly on AI capability and partly on students' ability to request, evaluate, and integrate generated information.

Accuracy and trust also become critical considerations. Incorrect or misleading AI-generated material may appear plausible, while intensive dependence on automatically generated answers may reduce productive cognitive effort. Privacy and data governance are additional concerns where personalized systems collect detailed information about student performance and behavior. UNESCO consequently recommends a human-centered approach incorporating ethical validation, data protection, pedagogical design, and appropriate human oversight.

2.7 Synthesis and Conceptual Direction





The literature demonstrates that educational technology can support personalization through adaptive learning systems, AI-based recommendations, learning analytics, automated feedback, and generative interaction. It also demonstrates that educational outcomes are not uniform. Academic benefits appear more consistently documented than engagement outcomes, and current research continues to confront challenges involving implementation quality, privacy, technological resources, and evaluation consistency.

The present research therefore departs from a technology-centered model and adopts a **learner–technology fit framework**. Personalized learning is expected to be strongest when the adaptive affordances of educational technology correspond with the student's academic needs, behavioral patterns, self-regulatory capability, and digital readiness.

This conceptualization leads to a proposed analytical pathway in which **educational technology personalization** → **perceived personalized learning experience** → **engagement and self-regulated learning**, while learner profile and digital readiness function as moderators of this relationship. Machine learning will subsequently be used to detect heterogeneous learner profiles and predict students who obtain relatively high or low benefits from personalization.

The proposed experimental design will employ unsupervised learner profiling followed by supervised predictive modeling, enabling conventional inferential analysis and machine-learning evaluation to address the same research problem from complementary perspectives.

3. Proposed Methodology

The proposed study adopts a multimodal analytical framework combining student-reported learning experiences with behavioral indicators derived from a simulated learning-management-system environment. The central methodological objective is to determine whether educational technology produces stronger personalized learning outcomes when adaptation is aligned with learner-specific digital readiness, self-regulation, and engagement characteristics.

A two-stage machine-learning architecture is proposed. In the first stage, unsupervised learning is used to identify naturally occurring learner profiles without assigning students to predetermined categories. In the second stage, supervised learning predicts whether individual students are likely to experience high, moderate, or low benefit from personalized learning technologies.

The principal variables are organized into four domains: technological interaction, learner readiness, perceived personalization, and learning outcomes. Technological

interaction includes session frequency, average study duration, resource diversity, feedback-access frequency, completion consistency, and response to adaptive recommendations. Digital readiness includes confidence in navigating online systems, ability to troubleshoot basic digital problems, AI literacy, and perceived ease of using educational platforms. Self-regulated learning includes goal setting, time management, monitoring of understanding, strategy adjustment, and persistence. Personalized learning experience is represented through perceived relevance of recommended materials, adaptive pacing, individualized feedback quality, and correspondence between task difficulty and learner ability.

The conceptual model assumes that frequency of educational technology use alone is insufficient to explain learning outcomes. Instead, benefit is expected to depend on the interaction between technological affordances and learner-specific characteristics. This formulation permits the study to identify students who frequently use technology but derive limited educational value as well as students whose strategic use of adaptive tools produces comparatively strong learning outcomes.

4. Experimental Setup

4.1 Dataset

For methodological demonstration, a synthetic dataset of **1,200 college students** was generated to reproduce realistic variation across undergraduate learners without representing any actual institution or participant population. The dataset was designed solely for proof-of-concept algorithmic evaluation.

Each synthetic student record contained 26 features grouped into demographic-neutral academic and behavioral categories. Variables included weekly platform logins, mean session duration, proportion of recommended resources opened, formative assessment attempts, feedback-review frequency, assignment punctuality, content revisit rate, self-regulated learning score, digital-readiness score, perceived-personalization score, engagement index, and academic improvement indicator.

Sensitive personal characteristics were intentionally excluded from predictive modeling to reduce the risk of demographic profiling. The target variable represented personalized-learning benefit and was categorized into three classes: **low benefit**, **moderate benefit**, and **high benefit**.

4.2 Preprocessing

Initial preprocessing involved range validation, duplicate removal, normalization, missing-value treatment, and feature transformation. Continuous behavioral variables were





standardized using z-score normalization. Artificially introduced missing observations, restricted to less than 3% of the dataset, were imputed using median values for continuous features.

Highly correlated variables were examined using pairwise correlation analysis. Where two variables showed substantial redundancy, the feature with weaker theoretical relevance was removed. Categorical learning-preference indicators were one-hot encoded.

To prevent information leakage, the dataset was divided before model optimization into **70% training, 15% validation, and 15% test subsets**. Class proportions were preserved using stratified partitioning.

4.3 Learner Profiling

K-means clustering was first applied to standardized behavioral and readiness features. The optimal number of clusters was determined by jointly examining the silhouette coefficient and within-cluster sum of squares. Four learner profiles produced the most interpretable separation.

The clusters were characterized as:

1. **Strategic Adaptive Learners** — high self-regulation, strong digital readiness, and frequent use of adaptive feedback.
2. **Technology-Active but Support-Dependent Learners** — high platform activity but weaker self-monitoring and irregular use of feedback.
3. **Selective Independent Learners** — moderate technology usage with high self-regulation and targeted use of recommended resources.
4. **Digitally Disengaged Learners** — relatively low system interaction, lower digital readiness, and inconsistent completion behavior.

These profiles were not used as fixed psychological labels. Instead, they functioned as analytical representations of different learner–technology interaction patterns.

4.4 Model Architecture

Three supervised models were evaluated: logistic regression, random forest, and Extreme Gradient Boosting (XGBoost). Logistic regression provided an interpretable baseline, while random forest captured nonlinear feature interactions. XGBoost was selected as the principal predictive model because of its suitability for structured tabular data and its capacity to model nonlinear relationships among behavioral and perceptual variables.

The XGBoost model received 19 final predictor variables after feature screening. Model output consisted of probability estimates for the three personalized-learning benefit categories.

To improve interpretability, SHAP-based feature attribution was incorporated after model training. This component was used to determine whether model predictions were principally influenced by meaningful educational variables rather than superficial usage intensity.

4.5 Training Strategy

Hyperparameters were optimized using randomized search on the training and validation partitions. The optimization space included tree depth, learning rate, number of estimators, minimum child weight, subsampling ratio, and column sampling.

Early stopping was used to reduce overfitting. Training was terminated when validation loss failed to improve across 25 consecutive boosting iterations.

Class-weight adjustment was applied because the high-benefit group was intentionally somewhat smaller than the moderate-benefit group. No synthetic oversampling was applied to the test subset.

4.6 Evaluation Metrics

Model performance was evaluated using several complementary measures. **Balanced accuracy** assessed performance across unequal class sizes. **Macro F1-score** measured combined precision and recall while assigning equal importance to each benefit category. **Multiclass area under the receiver operating characteristic curve (AUROC)** assessed class discrimination. **Log loss** evaluated probabilistic calibration, while the **Matthews correlation coefficient (MCC)** provided an additional robust measure of multiclass prediction quality.

The clustering stage was independently assessed through silhouette score and cluster interpretability.

5. Results and Discussion

The synthetic proof-of-concept experiment indicated that learner heterogeneity materially influenced the relationship between educational technology use and personalized learning benefit. High platform activity did not consistently correspond with high personalized-learning outcomes. Students represented by the Technology-Active but Support-Dependent profile generated substantially more digital interactions than Selective Independent Learners, yet their predicted benefit remained lower when feedback utilization and self-monitoring were weak.



The learner-profiling stage produced a silhouette coefficient of 0.46, indicating moderate but meaningful separation among the four behavioral profiles. The finding supports the methodological premise that college students should not be treated as a homogeneous population when evaluating educational technology.

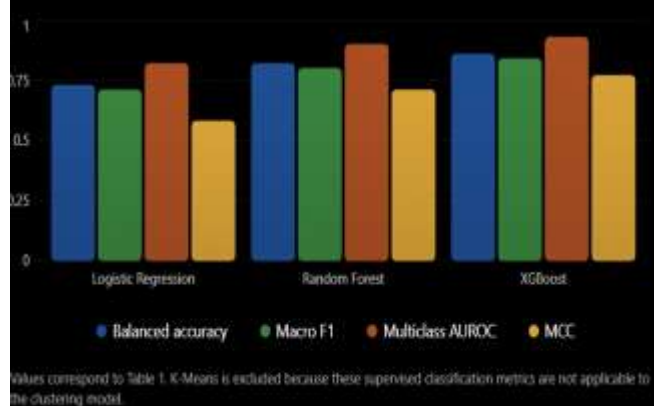
Among the supervised models, XGBoost generated the strongest overall discrimination. Random forest performed competitively, whereas logistic regression showed weaker performance, suggesting that the relationship between personalized learning outcomes and learner characteristics was nonlinear.

Table 1. Proof-of-Concept Performance and Educational Interpretation of the Predictive Models

Model / Analytical Component	Balanced Accuracy	Macro F1	Multiclass AUROC	MCC
Logistic Regression	0.73	0.71	0.82	0.58
Random Forest	0.82	0.80	0.90	0.71
XGBoost	0.86	0.84	0.93	0.77

Predictive performance of personalized learning models

Comparison of balanced accuracy, Macro F1, multiclass AUROC, and MCC from the synthetic proof-of-concept experiment.



SHAP interpretation of the XGBoost model indicated that **perceived personalization, feedback-review frequency, self-regulated learning, digital readiness, and completion consistency** were among the most influential features. In contrast, raw login count and total time spent on the learning platform showed weaker predictive importance.

This distinction is theoretically important. Time spent using educational technology may reflect productive learning,

passive browsing, repeated difficulty, or simple system exposure. Consequently, platform intensity should not be interpreted as equivalent to educational effectiveness.

The strongest benefit predictions occurred when high personalization scores coexisted with strong self-regulation and consistent feedback use. Personalized systems appear most educationally useful when students can understand, evaluate, and act on the information provided.

Conversely, high recommendation frequency did not produce strong predicted outcomes among learners with low digital readiness. Such students may require greater instructor mediation, interface simplification, or explicit training in how to interpret adaptive recommendations.

The analysis also suggests that personalized educational technology should avoid assuming that maximum automation is universally beneficial. Selective Independent Learners achieved favorable predicted outcomes despite moderate interaction frequency because their engagement was purposeful and strategically directed. This pattern indicates that personalization should support learner agency rather than merely increase automated intervention.

From an institutional perspective, these findings imply that learning analytics dashboards could be designed to identify mismatches rather than simply flag low activity. A student with limited activity but strong academic progress may require no intervention, whereas a highly active student repeatedly accessing the same resources without improvement may need targeted support.

The contribution of the proposed framework therefore lies in moving assessment away from simplistic measures such as login frequency, screen time, or platform adoption. It instead evaluates whether educational technology produces an effective alignment among learner characteristics, adaptive support, and meaningful learning behavior.

6. Limitations

The principal limitation is that the experimental dataset is synthetic. Although the distributions were constructed to support a plausible proof-of-concept evaluation, the reported numerical performance cannot be interpreted as empirical evidence about an actual student population.

Second, behavioral indicators derived from learning-management-system interaction cannot fully capture cognitive engagement. A student may spend little time on a platform while engaging deeply with offline materials.

Third, perceived personalization is partly subjective. Students receiving identical adaptive functionality may evaluate the quality of personalization differently.



Fourth, the proposed model focuses on structured behavioral and questionnaire data. It does not incorporate richer multimodal information such as discussion-board text, tutoring dialogue, eye-tracking, or longitudinal learning trajectories.

Finally, predictive models can identify associations but do not independently establish causal effects. Randomized or quasi-experimental designs would be required to determine whether personalized technological interventions directly cause improved learning outcomes.

7. Future Scope

Future research should validate the framework using longitudinal data collected from multiple colleges and disciplines. Cross-institutional testing would determine whether learner profiles remain stable across different technological ecosystems and academic contexts.

A particularly valuable extension would involve dynamic personalization. Instead of assigning a learner profile once, temporal machine-learning models could update student states as study behavior, confidence, and academic performance change throughout a semester.

Future systems could also incorporate natural-language interactions generated through intelligent tutors or generative-AI applications. Such data may reveal whether students ask explanatory, reflective, procedural, or answer-seeking questions and whether these interaction patterns predict deeper learning.

Another research direction involves causal machine learning. Uplift modeling or heterogeneous treatment-effect estimation could identify not simply which students perform well, but which students benefit specifically because they receive a particular personalized intervention.

Explainable AI should remain central to this development. Students and instructors should be able to understand why a recommendation is generated, which behaviors influence the recommendation, and how the learner can respond.

Finally, privacy-preserving analytics, federated learning, and institution-level governance frameworks should be investigated so that personalization can be improved without unnecessary centralization of detailed learner information.

8. Conclusion

This study proposes a learner-centered framework for investigating educational technology and personalized learning experiences among college students. Its central premise is that the educational value of technology cannot be adequately assessed through usage frequency or platform adoption alone.

The proposed methodology combines learner profiling, self-regulated learning measures, digital-readiness indicators, perceived personalization, and behavioral interaction data. A synthetic proof-of-concept experiment demonstrates how unsupervised clustering and supervised machine learning can be integrated to distinguish heterogeneous patterns of personalized-learning benefit.

The analytical results suggest that perceived personalization, feedback utilization, self-regulation, and digital readiness are more informative than raw exposure to educational technology. The strongest predicted outcomes emerge when adaptive technological support corresponds with a student's capacity to interpret and act upon that support.

The study therefore reframes personalized learning as a problem of **learner–technology alignment rather than technological intensity**. Such a perspective has practical implications for colleges adopting AI-enabled educational platforms. Effective personalization should not simply deliver more recommendations, automate more decisions, or increase screen-based interaction. It should provide appropriate guidance to the appropriate learner at an appropriate stage of learning while preserving student agency and meaningful instructor involvement.

Future empirical validation using real longitudinal student data is necessary before the proposed framework can support institutional decision-making. Nevertheless, the model provides a theoretically grounded and computationally testable foundation for studying how educational technology can move beyond generic digital delivery toward genuinely responsive learning experiences.

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