Learner Readiness for Personalized Learning in Higher Education: A Scoping Review of Conceptualizations and Measurement Approaches

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ABSTRACT

Personalized learning is increasingly supported by artificial intelligence, learning analytics, adaptive learning systems, and other digital technologies in higher education. However, the effectiveness of personalized learning also depends on whether learners are prepared to manage, regulate, and sustain their learning. This scoping review examined how personalized learning readiness (PLR) has been conceptualized and measured in higher education. Searches were conducted in Scopus, Web of Science Core Collection, China National Knowledge Infrastructure (CNKI), and ERIC. After deduplication, 601 unique records were screened, and 24 studies published between 2017 and 2026 were included. Only two studies directly examined PLR, while the remaining 22 provided contextual evidence through related constructs such as digital and technological readiness, digital competence, self-directed learning, self-regulated learning, learning autonomy, learning preferences, technology acceptance, and trust. Existing measurement approaches were grouped into four broad types: direct PLR assessment, adaptation of related readiness measures, indirect assessment through learner-process constructs, and behavioral or outcome indicators. No common PLR definition or measurement instrument was repeatedly used across the included studies. Based on the evidence, PLR is best understood as learners' psychological and behavioral readiness to manage their learning, make learning decisions, and sustain participation in personalized learning. Future research should develop and validate PLR-specific measures and examine their predictive value across longitudinal and cross-cultural contexts.

Keywords: personalized learning readiness, higher education, personalized learning, learner readiness, scoping review

INTRODUCTION

With the deeper development of digital transformation in higher education, technologies such as online learning platforms, learning analytics, adaptive learning, and generative artificial intelligence enable universities to more accurately identify the differences among students in terms of their learning needs, abilities, interests, and progress. This allows them to provide more targeted content, pathways, resources, and feedback. In this context, personalized learning has become an important teaching method in higher education. It emphasizes adjusting the learning process based on individual differences and progress, while also encouraging students to participate in learning decisions and actively manage their own learning. Therefore, personalized learning not only reflects the

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transformation of teaching methods supported by digital technology, but also serves as a key direction for promoting reforms in higher education teaching.

For the purposes of this review, personalized learning is understood as an approach in which learning content, pathways, resources, pace, or feedback are adjusted to individual learner characteristics while learners retain an active role in learning decisions and self-management. Related approaches were treated as conceptually overlapping but not identical. Adaptive learning primarily refers to data- or system-driven adjustment, individualized learning emphasizes tailoring learning to individual needs or pace, and customized instruction refers more broadly to the modification of instructional provision. These approaches were included only when learner readiness or a closely related learner condition relevant to participation in personalized learning was examined within a clear personalized learning context.

However, the external support provided by technology and instructional design does not automatically ensure successful personalized learning. Its effectiveness also depends on whether students have the necessary readiness to engage in personalized learning. Compared to teacher-directed teaching methods, personalized learning gives students more choices and autonomy; however, it also requires them to take on more learning responsibilities, such as setting goals, managing their time, choosing appropriate strategies, and monitoring their progress. Therefore, a student’s willingness to participate in personalized learning, as well as their ability to manage and control their own learning, are important factors that determine the effective implementation of personalized learning. These factors also form the basis for discussing a student’s readiness for personalized learning.

Existing research uses similar concepts such as learner readiness, self-directed learning readiness, online learning readiness, and digital learning readiness, but their definitions, dimensions, and measurement methods vary. In higher education, it remains unclear which characteristics constitute elements of personalized learning readiness, and which should be considered separate concepts such as self-regulated learning, digital skills, or technology acceptance. Most reviews focus on technical systems, teaching models, and learning outcomes, without providing a systematic analysis of learner readiness and its measurement. Therefore, this study adopts a scoping review approach to examine how PLR has been conceptualized and measured in higher education. The review maps direct PLR evidence together with contextual evidence from related learner constructs, while maintaining clear conceptual boundaries between PLR and adjacent constructs such as SRL, SDL, digital competence, and technology acceptance. It also compares the available measurement approaches and psychometric evidence and maps variables associated with learner preparedness to identify priorities for future research.

MATERIALS AND METHODS

Inclusion and Exclusion Criteria

This scoping review was guided by the JBI methodological guidance for scoping reviews [19] and reported in accordance with the PRISMA extension for Scoping Reviews (PRISMA-ScR) [25]. Eligibility criteria were structured using the Population–Concept–Context (PCC) framework. The population comprised learners in higher education; the concept referred to the readiness required for learners to participate in, manage, and sustain personalized learning activities; and the context comprised personalized, individualized, customized, or closely related adaptive learning environments in higher education. Based on this framework, the inclusion and exclusion criteria were defined before study selection.

The inclusion criteria include: ① The study subjects are undergraduate students, postgraduate students, or other individuals pursuing higher education; if the study covers multiple educational stages, the results related to higher education must be able to be extracted separately. ② The study discusses the readiness of learners or related concepts of readiness within a clear personalized learning context. ③ The study must report at least one

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aspect such as concept definition, dimensions of composition, measurement tools, levels of readiness, influencing factors, or relevant variables. ④ The literature types include published quantitative studies, qualitative studies, mixed-method studies, or studies on the development and validation of measurement tools. ⑤ The report was published in Chinese or English and a full text could be retrieved for eligibility assessment.

The exclusion criteria include: ① The study subjects are only primary and secondary school students, teachers, parents, administrators, educational institutions, or technical systems, and it is not possible to extract results related to higher education learners separately. ② The study focuses solely on teacher, organization, or technical readiness. ③ The study deals with online learning, digital learning, artificial intelligence, or technology acceptance, but it is not clearly situated within a personalized learning context. ④ The study discusses instructional design, platforms, algorithms, or learning outcomes, but it does not define, measure, or analyze learner readiness. ⑤ The report was a review, commentary, editorial, book review, news article, research proposal, duplicate record, or was published in a language other than Chinese or English. Reports whose full texts could not be retrieved were recorded separately as "reports not retrieved" and were not counted as full-text exclusions. No publication-year restriction was applied.

Literature Search

The searches were conducted in Scopus, Web of Science Core Collection, China National Knowledge Infrastructure (CNKI), and ERIC. For the English search, keywords related to personalized/individualized learning, learner readiness, self-directed or self-regulated learning, and higher education were used. In the Chinese search, the term "personalized learning" served as the core keyword, along with terms such as "readiness", "learning preparation", "learner readiness", and "self-directed learning". The searches in Scopus, Web of Science, and CNKI were completed on August 5, 2026, while the search in ERIC was completed on August 15, 2026. A total of 555 records were obtained from the first three databases; after removing duplicates, 410 records remained. From the two sets of records obtained from ERIC, 218 records were identified, and after combining these with existing records, 191 unique records were added. Ultimately, 601 unique records entered title and abstract screening. The specific search strategies and results are presented in Table 1.

Table 1: Complete Search Strategies and Results by Database

Database/ID	Search strategy/field	n
Scopus S1	("personalized learning" OR "personalised learning") AND (readiness OR preparedness) Field: Article Title, Abstract, Keywords	344
Scopus S2	("individualized learning" OR "individualised learning" OR "customized learning" OR "customised learning") AND (readiness OR preparedness OR "learner readiness" OR "student readiness" OR "self-directed learning readiness") AND ("higher education" OR universit* OR college* OR undergraduate*) Field: Article Title, Abstract, Keywords	31
Web of Science W1	("personalized learning" OR "personalised learning") AND (readiness OR preparedness) Field: Topic	149
Web of Science W2	("individualized learning" OR "individualised learning" OR "customized learning" OR "customised learning") AND (readiness OR preparedness) AND ("higher education" OR universit* OR college* OR undergraduate*) Field: Topic	22

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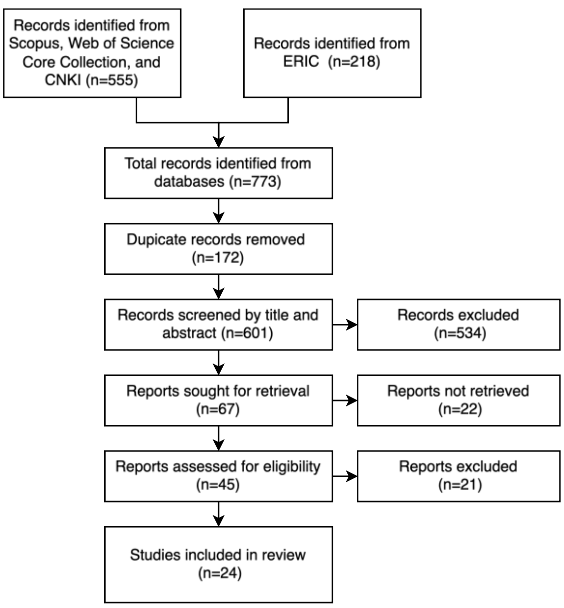
Database/ID	Search strategy/field	n
CNKI Z1	Subject = personalized learning AND Subject = readiness	1
CNKI Z2	Subject = personalized learning AND Subject = learning readiness	2
CNKI Z3	Subject = personalized learning AND Subject = learner readiness	1
CNKI Z4	Subject = personalized learning AND Subject = self-directed learning	5
ERIC E1	Personalized/individualized learning × readiness/preparedness/learner readiness/student readiness; combined search across ERIC titles, abstracts, and subject terms	94
ERIC E2	Personalized/individualized learning × self-directed/self-regulated learning/autonomy/readiness × higher education/college/university; combined search across ERIC titles, abstracts, and subject terms	124

Literature Screening

The references identified through the database searches were imported into EndNote 2025 for management. Duplicate records were identified using title, author, publication year, and DOI, followed by manual verification of standardized titles. The database searches yielded 773 records in total, including 555 records from Scopus, Web of Science Core Collection, and CNKI and 218 records from ERIC. After duplicate removal, 601 unique records remained for title and abstract screening.

Records were then screened according to the predefined eligibility criteria. A total of 534 records were excluded during title and abstract screening, leaving 67 reports for which full texts were sought. Full texts could not be retrieved for 22 reports. The remaining 45 reports underwent full-text eligibility assessment. Of these, 21 reports were excluded because they did not meet the predefined eligibility criteria, and 24 studies were included in the final evidence synthesis. Final study-selection categories were treated as mutually exclusive for PRISMA-ScR reporting [25]. The study-selection process is presented in Figure 1.

Figure 1. PRISMA-ScR flow diagram of the study-selection process



Data Extraction and Synthesis

A data extraction table was created using Microsoft Excel. Information such as authors, years, country or region, subjects of study, sample size, research design, personalized learning contexts, terms and definitions related to readiness, dimensions of the study, measurement tools, number of items, scoring methods, reliability and validity information, and main findings were extracted. Descriptive statistics were used to summarize the characteristics of the studies, and content analysis was employed to define concepts and determine measurement methods. Variables related to readiness were only briefly presented; no effect sizes were combined. Because the purpose of this scoping review was to map conceptualizations and measurement approaches rather than to estimate intervention effects, a formal risk-of-bias assessment was not conducted. Instead, available information on measurement quality was extracted and compared across studies. This included pilot testing, internal consistency reliability, factor analysis, construct validity, composite reliability, convergent validity, and other reported psychometric evidence where available. Measurement evidence was interpreted as support for the construct originally assessed by each instrument and not automatically as evidence of validity for PLR.

RESULTS

Literature Screening Results

The searches across Scopus, Web of Science Core Collection, CNKI, and ERIC yielded 773 records. After duplicate removal, 601 unique records remained for title and abstract screening. Of these, 534 records were excluded, leaving 67 reports for which full texts were sought. Twenty-two reports could not be retrieved. The remaining 45 reports underwent full-text eligibility assessment, of which 21 were excluded and 24 studies were included in the final evidence synthesis.

Among the 24 included studies, only two directly examined personalized learning readiness. The remaining 22 studies provided contextual evidence through related learner constructs and personalized, individualized, or adaptive learning contexts, including digital and technological readiness, digital competence, self-directed learning, self-regulated learning, learning autonomy, learning preferences, technology acceptance, and trust.

Basic Characteristics of the Studies Included in the Research

A total of 24 studies published between 2017 and 2026 were included. Eighteen studies (75.0%) were published between 2024 and 2026, indicating that most of the available evidence remains recent and has developed alongside rapid advances in AI, learning analytics, and adaptive learning.

The studies covered at least 12 countries and were concentrated mainly in Asia and Eastern Europe, although evidence was also identified in other regions. Some studies did not clearly report the country in which the study sample was recruited; therefore, study location was not inferred solely from author affiliation. Research designs included cross-sectional surveys, correlational studies, SEM, mixed methods, experiments, scale validation, learning analytics, and qualitative approaches. Sixteen studies reported verifiable sample sizes, involving at least 4,139 higher education students.

The research contexts included AI-supported adaptive learning, machine-learning-based personalization, learning analytics, AI chatbots, automated feedback, flipped classrooms, mobile learning, flexible learning environments, personalized language learning, and personalized learning analytics dashboards. Detailed study characteristics are presented in Table 2.

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Table 2: Characteristics of the Included Studies

Study	Country	Participants and sample	Design	Personalized learning context	Evidence type
Omirali et al. (2025)	Kazakhstan	150 undergraduates	Cross-sectional survey	Proposed proactive AI multi-agent system in a Canvas environment	Contextual
Hussan et al. (2024)	Malaysia	Survey n = 145; interviews n = 18	Sequential mixed methods	Learning analytics supporting individualized learning pathways and resource recommendations	Contextual
Muslihati et al. (2022)	Indonesia	First-year university students; NR	Descriptive survey	Personalized learning system for academic support of first-year students	Contextual
Shamsudin & Cao (2025)	Malaysia	400 ODL students	Survey; PLS-SEM	Machine-learning-enabled personalized learning	Contextual
Rakhmetov et al. (2026)	Kazakhstan	Higher education students; NR	Platform pilot; learning analytics and SEM	AI-supported distance-learning platform, adaptive trajectories, and personalized feedback	Contextual
Krasnopolskyi et al. (2024)	Ukraine	100 first-year students	Teaching experiment	Personal educational trajectories for individualized foreign-language learning	Contextual
Kubincová & Miková (2025)	Slovakia	Teachers and students; NR	Comparative survey	Personalized virtual learning environment	Direct PLR
Elfaiz et al. (2025)	Indonesia	356 university students	Survey; K-means clustering	Personalized learning based on learner profiles	Direct PLR
Alsaffar (2025)	Kuwait	296 university students	Survey; SEM	AI-driven adaptive multimedia and personalized learning pathways	Contextual
Poznanskyy et al. (2025)	Ukraine	320 prospective foreign-language teachers	Survey and teaching experiment	AI-adaptive foreign-language learning and personalized feedback	Contextual
Chanyawudhiwan & Mingsiritham (2026)	Thailand	378 undergraduates	Survey; CB-SEM	AI-supported intelligent nano-learning platform	Contextual
Shermanova & Taylakova (2026)	Uzbekistan	Higher education students; NR	Mixed methods; experimental/control	AI tools, digital literacy, and personalized learning pathways	Contextual
Kondrateva et al. (2023)	Russia	University students; NR	Pedagogical/implementation study	Interactive technologies, learning motivation, and personalized learning pathways	Contextual

Study	Country	Participants and sample	Design	Personalized learning context	Evidence type
Alvarez & Angeles (2025)	Philippines	Students; NR	Mixed methods; hierarchical regression	Khanmigo AI platform and personalized learning	Contextual
Lee (2026)	Malaysia	Students; NR	Mixed methods	AI learning assistant, individualized support, and timely feedback	Contextual
Koh & Kan (2021)	NR	262 university art students	Survey	Personalized adaptive learning in a next-generation digital learning environment	Contextual
Mukherjee & Singh (2026)	NR	200 university students	Cross-sectional survey; PCA/regression	AI chatbots supporting self-directed and personalized learning	Contextual
Li & Kim (2024)	Australia	Survey n = 32; e-portfolio n = 7	Qualitatively driven mixed methods	Automated feedback supporting personalized English-learning trajectories	Contextual
Bui et al. (2022)	NR	155 engineering students	Pre-post experiment	Flipped classroom supporting personalized learning	Contextual
Ma & Chiu (2024)	NR	35 university students	Exploratory mixed methods	Self-regulated and collaborative personalized vocabulary learning in MALL	Contextual
Fujii (2024)	Japan	849 university students	Survey; correlational analysis	Technology-supported flexible and individualized learning environment	Contextual
Harati et al. (2020)	NR	University students; NR	Scale development and validation	Online adaptive learning environment	Contextual
Zhang & Yang (2025)	NR	420 college students	Quantitative survey	Technology-supported personalised language learning; digital literacy, engagement, motivation, and adaptation to PL tools	Contextual
Roberts et al. (2017)	NR	Focus groups n = 41; survey sample NR	Exploratory multi-method study	Personalized learning analytics dashboards, learner preferences, control, and customization	Contextual

Note. PLR = personalized learning readiness; ODL = open and distance learning; NR = not reported or not verifiable from the available published record or exported metadata. Country information was reported only when explicitly supported by the available record and was not inferred from author names or other indirect information.

Terminology and conceptual definitions related to learner readiness

Among the 24 included studies, only two directly examined readiness for personalized learning. Elfaiz et al. [5]

conceptualized student readiness in terms of learning adaptability, motivation, perceived value of learning, and technical proficiency, and used clustering to identify different readiness profiles. Kubincová and Miková [12] assessed readiness for personalized learning environments by comparing teacher and student preferences for learning materials, technologies, and teaching methods.

The remaining 22 studies provided contextual evidence through related constructs, including technological and digital readiness, digital competence, AI acceptance, self-directed and self-regulated learning, learning autonomy, learning preferences, learning analytics acceptance, and adaptation to personalized environments. For example, Zhang and Yang [27] examined digital literacy, motivation, engagement, and adaptation to personalized learning tools, while Roberts et al. [22] examined student preferences, customization, and learner control in personalized learning analytics dashboards. These studies provide evidence about conditions associated with participation in personalized learning, but they do not establish these constructs as equivalent measures of PLR. Overall, no unified definition or dimensional structure of PLR has yet been established.

Dimensions and measurement methods

Existing measurement approaches can be grouped into four types. First, a small number of studies directly assess PLR using indicators such as motivation, learning preferences, and technical skills, usually through self-developed instruments. Second, some studies adapt measures of technological or digital readiness, AI readiness, learning analytics acceptance, trust, and technology acceptance. Third, constructs such as self-directed learning, self-regulated learning, autonomy, and learning preferences are used to indirectly represent students' capacity to engage in personalized learning. Fourth, behavioral and outcome indicators, including platform use, course preferences, learning performance, and pre–post changes, are used as indirect measures. Although Harati et al. [7] developed the Adaptive Self-Regulated Learning Questionnaire (ASRQ), it measures self-regulated learning in adaptive environments rather than PLR. Overall, no common PLR instrument has been repeatedly used across the 24 studies.

Table 3: Readiness Terms and Measurement Approaches in the Included Studies

Study	Term and evidence type	Operationalization	Items, scoring, and measurement evidence
Omirali et al. (2025)	AI-use readiness; contextual	Self-developed survey: usefulness, trust, value, privacy, autonomy	5-point; α=.77–.83; readiness α=.83
Hussan et al. (2024)	Learning analytics readiness; contextual	Adapted survey + interviews: awareness, comfort, usefulness, data handling	Pilot n=10; face validity; α NR
Muslihati et al. (2022)	Academic/self-regulatory readiness; contextual	Survey: anxiety, SRL, writing skills, support needs, media preferences	NR
Shamsudin & Cao (2025)	Technology readiness; contextual	Survey of TR, ML competence, personalized learning, engagement, performance	α, CR, AVE, Fornell–Larcker reported
Rakhmetov et al. (2026)	Initial digital readiness; contextual	Digital competence/training groups + learning analytics	Scale and psychometrics NR
Krasnopolskyi et al. (2024)	Personal-trajectory readiness; contextual	Agency, attitudes, motivation + educational-trajectory experiment	No PLR measure; psychometrics NR

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Study	Term and evidence type	Operationalization	Items, scoring, and measurement evidence
Kubincová & Miková (2025)	Personalized learning environment readiness; direct PLR	Teacher–student preferences for materials, technology, and methods	Items/scoring/psychometrics NR
Elfaiz et al. (2025)	Personalized learning readiness; direct PLR	21-item self-developed survey + K-means profiles	5-point; pilot n=39; α=.79
Alsaffar (2025)	Learner digital readiness; contextual	Adapted online readiness, digital literacy, and SDL measures	Pilot n=30; α=.91; CR=.94; AVE=.73
Poznanskyy et al. (2025)	AI-use readiness; contextual	Motivation, cognition, and activity components	Psychometrics NR
Chanyawudhiwan & Mingsiritham (2026)	User readiness and trust; contextual	Survey of quality, experience, environment, data, AI support, readiness	About 5 items per construct; 5-point; pilot n=30; α=.82–.90
Shermanova & Taylakova (2026)	Digital competence/AI learning readiness conditions; contextual	DigComp 2.2 assessment + interviews/focus groups	No PLR measure
Kondrateva et al. (2023)	Motivational and self-reflective readiness; contextual	Motivation, technology use, and self-reflection	NR
Alvarez & Angeles (2025)	AI adoption readiness; contextual	Survey + interviews on Khanmigo acceptance and perceptions	Psychometrics NR
Lee (2026)	Digital readiness; contextual	Survey, performance data, and interviews on AI learning assistants	Implementation condition; no PLR measure
Koh & Kan (2021)	Readiness for next-generation digital learning environments; contextual	LMS use and expected e-learning experience	n = 262; No PLR measure
Mukherjee & Singh (2026)	AI chatbot adoption/SDL; contextual	Survey; PCA and regression of usability, ethics, and barriers	n=200; psychometrics NR
Li & Kim (2024)	Autonomy/self-regulation; contextual	E-portfolios, focus groups, surveys on feedback and regulation	n=7/32; no PLR measure
Bui et al. (2022)	SDL/personalized learning; contextual	Pre–post SDL, personalized learning, engagement, evaluation	n = 155; psychometrics NR
Ma & Chiu (2024)	SRL/collaborative personalized learning; contextual	Pre–post survey, vocabulary test, interviews	n=35; no PLR measure

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Study	Term and evidence type	Operationalization	Items, scoring, and measurement evidence
Fujii (2024)	Autonomy support and learning preferences; contextual	Survey of autonomy, modality preference, strategies, GPA	n=849; indirect readiness
Harati et al. (2020)	Adaptive SRL; contextual	ASRQ for multidimensional SRL in adaptive learning	Expert review; α and CFA; not PLR-specific
Zhang & Yang (2025)	Digital literacy/adaptation to PL tools; contextual	Structured questionnaire examining digital literacy, language proficiency, engagement, motivation, and adaptation to personalized learning tools	n = 420; β = .841, p < .001; item-level scoring and psychometric evidence NR in the verified record
Roberts et al. (2017)	Learner preferences, control, and learning-analytics acceptance; contextual	Focus groups, student-generated dashboard designs, and survey data examining preferences, privacy, alerts, customization, and learner control	Focus groups n = 41; no PLR-specific instrument; survey psychometrics NR

Note. TR = technology readiness; ML = machine learning; LDR = learner digital readiness; ASRQ = Adaptive Self-Regulated Learning Questionnaire; CFA = confirmatory factor analysis; CR = composite reliability; AVE = average variance extracted. The table reports only information verified in the available published records or the reviewed manuscript. NR indicates that item, scoring, or reliability/validity information was not reported; no assumptions were made.

The quality of measurement also varies considerably. Some studies reported internal consistency, measurement-model validation, or confirmatory factor analysis [18], [5], [2], [23], [4], [7], whereas others relied mainly on acceptance surveys, preference measures, interviews, behavioral data, or learning outcomes. These approaches often assess related constructs such as SRL, SDL, digital competence, technology acceptance, trust, or learning preferences rather than independently validated PLR.

The reviewed measures also differed in their target constructs and applicability to PLR in higher education. Direct PLR measures were limited to two studies and were based on context-specific readiness profiles or preferences rather than a repeatedly validated higher education instrument. Other instruments were originally designed to assess digital readiness, technology readiness, technology acceptance, learning analytics acceptance, SDL, SRL, autonomy, digital literacy, or related constructs. Therefore, reported reliability and validity evidence supports the original constructs assessed by these instruments but does not establish their validity as measures of PLR. This distinction limits direct comparison of readiness scores across studies and reinforces the need for a PLR-specific measurement framework.

Variables Related to Learners' Preparedness

Existing studies mainly associate learner preparedness with digital and technological readiness, digital competence, self-regulation and autonomy, trust and ethics, learning preferences, motivation, and learning outcomes. Digital or technological preparedness and competence have been linked to personalized learning paths, platform use, academic performance, adoption intentions, engagement, and adaptation to personalized learning tools, although these relationships are context dependent [2], [23], [4], [21], [27]. LMS experience, AI usability, ethical concerns, learning analytics preferences, and perceptions of AI platforms also influence students' expectations and use of personalized digital environments [9], [16], [1], [22].

Learner-related factors are equally important. Self-direction, self-regulation, autonomy, learning preferences, learner control, and feedback use have been associated with engagement and learning processes in personalized environments [3], [15], [14], [6], [7], [22]. Privacy, security, and trust may further support or constrain students' acceptance and use of such environments [18], [8], [22]. Overall, preparedness is related to multiple learner and contextual factors, but these constructs should not be treated as equivalent to PLR.

Table 4: Learner-Readiness-Related Factors Examined in the Included Studies

Evidence theme	No. of studies	Main direction	Representative studies
Direct PLR/readiness for personalized learning environments	2	Directly describes or distinguishes students' readiness profiles or readiness states for personalized learning	Elfaiz et al.; Kubincová & Miková
Digital and technological readiness, competence, AI, and user acceptance	14	Generally shows positive or context-dependent relationships with pathway optimization, platform use, learning engagement, adoption intention, or learning performance	Omirali et al.; Hussan et al.; Shamsudin & Cao; Rakhmetov et al.; Alsaffar; Chanyawudhiwan & Mingsiritham; Shermanova & Taylakova; Alvarez & Angeles; Lee; Koh & Kan; Mukherjee & Singh; Poznanskyy et al.; Zhang & Yang; Roberts et al.
Self-regulation, self-direction, and learner autonomy	12	Supports management and sustained participation; distinct from PLR.	Muslihati et al.; Krasnopolskyi et al.; Elfaiz et al.; Poznanskyy et al.; Koh & Kan; Mukherjee & Singh; Li & Kim; Bui et al.; Ma & Chiu; Fujii; Harati et al.; Roberts et al.
Trust, privacy, ethics, and technical barriers	7	Trust and usability support adoption; privacy, security, ethical concerns, overreliance, and technical barriers constrain use	Omirali et al.; Hussan et al.; Chanyawudhiwan & Mingsiritham; Alvarez & Angeles; Lee; Mukherjee & Singh; Roberts et al.
Learning preferences, motivation, agency, and teacher-student perceptions	10	Motivation, preferences, autonomy, and differences in teacher-student perceptions influence how personalized opportunities are used and what support is needed	Krasnopolskyi et al.; Kubincová & Miková; Elfaiz et al.; Poznanskyy et al.; Kondrateva et al.; Koh & Kan; Li & Kim; Fujii; Zhang & Yang; Roberts et al.
Personalized system support and learning outcomes	13	Adaptive feedback, AI support, personalized pathways, flipped classrooms, and automated feedback are generally associated with improved engagement, strategy use, or performance	Shamsudin & Cao; Rakhmetov et al.; Krasnopolskyi et al.; Alsaffar; Chanyawudhiwan & Mingsiritham; Shermanova & Taylakova; Alvarez & Angeles; Lee; Bui et al.; Ma & Chiu; Fujii; Harati et al.; Zhang & Yang

Note. Studies may contribute to multiple themes; therefore, counts are not mutually exclusive.

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Overall, favorable learner conditions such as stronger digital competence, self-direction, self-regulation, autonomy, motivation, learning preferences, or technology acceptance were often associated with greater engagement with personalized learning opportunities. However, these constructs are conceptually and operationally heterogeneous and should not be interpreted as a single readiness score. Because the studies used different definitions, instruments, research designs, and predominantly cross-sectional or self-report data, the available evidence does not support a pooled estimate of PLR or a causal conclusion regarding its effects on learning outcomes.

DISCUSSION

Concept Definition and Boundaries

The findings indicate that PLR in higher education remains conceptually underdeveloped and requires clearer theoretical boundaries. Based on the reviewed evidence, PLR can be understood as a psychological and behavioral state in which students are able and willing to manage their learning, make learning decisions, and sustain participation in personalized learning. This definition emphasizes learning management, willingness, and sustained engagement. Accordingly, the heterogeneity identified in this review should not be interpreted as evidence that these constructs are interchangeable. Rather, it reflects the absence of an established PLR framework and explains why existing findings cannot yet be combined into a single readiness construct..

Related constructs should remain conceptually distinct from PLR. SRL concerns the regulation of learning processes, SDL emphasizes learner responsibility and initiative, digital competence reflects the ability to use digital technologies, and technology acceptance and trust concern willingness to use particular systems. These constructs may be associated with PLR and may support or constrain learners' readiness to engage in personalized learning. However, an association with PLR does not mean that these constructs are equivalent to PLR or constitute PLR itself. In other words, they may represent related learner characteristics, supporting conditions, or learning processes, but they should not be used interchangeably with PLR. Accordingly, the core of PLR should focus on learners' readiness to manage their learning, willingness to learn, and capacity to sustain goal-directed participation in personalized learning, while digital competence, technology acceptance, trust, and institutional support are better treated as related or contextual factors.

Measurement Methods and Situational Adaptability

The main challenge in PLR measurement is the inconsistency of what is being measured. Existing studies assess related constructs such as digital readiness, technology acceptance, trust, SRL, SDL, and learning preferences rather than PLR itself. Therefore, these measures cannot be directly combined into a unified PLR score. The two additional contextual studies reinforce this pattern. Zhang and Yang [27] examined digital literacy and adaptation to personalized learning tools rather than PLR itself, while Roberts et al. [22] examined learner preferences, customization, and control in personalized learning analytics dashboards rather than a readiness scale. These studies are informative for understanding conditions surrounding personalized learning, but they do not provide PLR-specific measurement instruments.

If PLR refers to learners' psychological and behavioral readiness to engage in personalized learning, measures related to self-directed learning readiness may provide a more appropriate basis, while technological factors should be treated separately. For example, the Personalised Learning Environment Questionnaire developed by Waldrip et al. [26] includes 12 self-directed learning readiness items covering self-management, desire for learning, and self-control, which are consistent with the ability and willingness to manage personalized learning. However, its factor structure, reliability, validity, and measurement invariance should be re-examined when applied to higher education or cross-cultural contexts.

Future studies should clearly report item sources and adaptation procedures and assess reliability, convergent and discriminant validity, and measurement invariance. Longitudinal or intervention studies are also needed to determine whether PLR predicts engagement, strategy use, and learning outcomes beyond SRL, SDL, digital competence, and technology acceptance. Such evidence is necessary to establish PLR as a distinct and meaningful construct.

Research Gaps and Implications for Higher Education

The 24 included studies were published between 2017 and 2026, with 18 appearing between 2024 and 2026. Although the evidence spans multiple countries and higher education contexts, its geographical distribution remains uneven and study location was not always clearly reported. Most studies rely on single-institution or course-based samples, cross-sectional surveys, or self-report data. Longitudinal and experimental evidence, specialized PLR measures, incremental validity, and cross-cultural measurement invariance remain limited. Some studies also assess expectations, digital competence, technology acceptance, or preferences toward emerging AI and learning-analytics systems rather than PLR itself, which limits direct comparison and causal interpretation.

Future research should distinguish PLR from contextual conditions and learning processes. A useful framework is "core readiness–contextual conditions–learning process–learning outcomes," in which PLR represents psychological and behavioral readiness, while digital competence, accessibility, AI trust, and privacy serve as contextual factors. Self-regulation, self-direction, and engagement represent learning processes. Longitudinal, multi-group, and cross-cultural studies are needed to examine change, subgroup differences, and structural comparability.

In practice, institutions should not equate digital familiarity or willingness to use AI with PLR. Readiness assessment should focus on learning management, willingness to learn, and self-control, while basic digital skills, learning preferences, platform experience, trust, privacy, and fairness should be assessed separately as contextual conditions. Its purpose should be to provide targeted support rather than to classify students into fixed categories.

Limitations of the Study

This review has four main limitations. First, the search was limited to Scopus, Web of Science Core Collection, ERIC, and China National Knowledge Infrastructure. Relevant studies indexed only in databases such as ProQuest, Education Source, PsycINFO, or regional databases may therefore have been missed. Second, full texts could not be retrieved for 22 potentially relevant reports. These reports could not undergo full-text eligibility assessment, and some may have met the inclusion criteria if their full texts had been available. Third, substantial conceptual and measurement heterogeneity was identified because many studies examined related constructs such as SRL, SDL, digital readiness, digital competence, learning autonomy, technology acceptance, learner preferences, or trust rather than PLR itself. This heterogeneity limits direct comparison across studies and prevents the interpretation of these constructs as equivalent measures of PLR. Fourth, consistent with the evidence-mapping purpose of this scoping review, no formal risk-of-bias assessment or effect-size synthesis was conducted. Instead, available psychometric and measurement-quality information was extracted and compared to characterize the strength and limitations of existing measurement approaches.

CONCLUSION

This scoping review included 24 higher education studies, only two of which directly examined personalized learning readiness. The remaining 22 studies provided contextual evidence through related constructs such as digital and technological readiness, digital competence, SDL, SRL, learning autonomy, learning preferences, technology acceptance, and trust. Overall, PLR lacks a unified definition and common measurement tool. Based on the reviewed evidence, PLR can be understood as students' psychological and behavioral readiness to manage their learning, make decisions, and sustain participation in personalized learning, while related constructs should retain their conceptual boundaries.

Across the contextual studies, more favorable learner conditions were often associated with greater technology acceptance, engagement, autonomous learning, and better learning outcomes, although the evidence is largely cross-sectional and context-specific. Future research should develop and validate clearly bounded PLR measures and test their predictive value through longitudinal, intervention, and cross-cultural studies. In practice, universities may assess readiness before implementing personalized learning and provide targeted support accordingly.

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REFERENCES

1. Alvarez, J. I., & Angeles, J. R. (2025). Khanmigo in the virtual classroom: A strategic evaluation through SWOT and acceptability analysis. Educational Process: International Journal, 16, e2025272. https://doi.org/10.22521/edupij.2025.16.272
2. Alsaffar, R. D. (2025). The role of AI-driven adaptive multimedia systems on personalized learning paths. Asian Journal of University Education, 21(2), 380–402. https://doi.org/10.24191/ajue.v21i1.26
3. Bui, T. T. H., Kaur, A., & Hung, T. V. (2022). A flipped classroom to personalise learning for engineering students. International Journal of Learning Technology, 17(2), 97–114. https://doi.org/10.1504/IJLT.2022.125082
4. Chanyawudhiwan, G., & Mingsiritham, K. (2026). User readiness and AI integration as drivers of smart nano learning in mobile environments. International Journal of Interactive Mobile Technologies, 20(10), 30–46. https://doi.org/10.3991/ijim.v20i10.60759
5. Elfaiz, E. A., Cinthya, M., Rinjeni, T. P., Pisi, B. A., Habibi, M. R., & Suroni, A. (2025). Profiling student readiness for personalized learning to support sustainable education. E3S Web of Conferences, 645, 06009. https://doi.org/10.1051/e3sconf/202564506009
6. Fujii, A. (2024). Exploring autonomy support and learning preference in higher education: Introducing a flexible and personalized learning environment with technology. Discover Education, 3, 26. https://doi.org/10.1007/s44217-024-00111-z
7. Harati, H., Yen, C.-J., Tu, C.-H., Cruickshank, B. J., & Armfield, S. W. J. (2020). Online adaptive learning: A study of score validity of the adaptive self-regulated learning model. International Journal of Web-Based Learning and Teaching Technologies, 15(4), 18–35. https://doi.org/10.4018/IJWLTT.2020100102
8. Hussan, F., Er, H. M., & Nadarajah, V. D. (2024). Health professions students' acceptance and readiness for learning analytics: Lessons for educators. BMC Medical Education, 24, 1347. https://doi.org/10.1186/s12909-024-06284-3

9. Koh, J. H. L., & Kan, R. Y. P. (2021). Students' use of learning management systems and desired e-learning experiences: Are they ready for next generation digital learning environments? Higher Education Research & Development, 40(5), 995–1010. https://doi.org/10.1080/07294360.2020.1799949
10. Kondrateva, I., Valeev, A., & Asmolovskaya, M. (2023). English language teaching methodology based on the development of students' motivation. Journal of Research in Applied Linguistics, 14(3), 252–256. https://doi.org/10.22055/rals.2023.19545
11. Krasnopolskyi, V., Tkachenko, I., Tsypina, D., Akimova, O., & Isakova, Y. (2024). Personalised and differentiated learning: The role of information environments in universities. Multidisciplinary Reviews, 7, e2024spe064. https://doi.org/10.31893/multirev.2024spe064
12. Kubincová, Z., & Miková, K. (2025). Personalization: Differences in teachers' and students' views. In Z. Kubincová, D. Durães, M. C. Sánchez-Gómez, P. Novais, L. Lancia, & M. A. Pellegrino (Eds.), Methodologies and intelligent systems for technology enhanced learning, workshops: 14th international conference (pp. 221–233). Springer. https://doi.org/10.1007/978-3-031-85561-0_18
13. Lee, B. N. (2026). Artificial intelligence as a learning assistant: A student-centered learning study. Cakrawala Pendidikan, 45(2), 351–361. https://doi.org/10.21831/cp.v45i2.94220
14. Li, L., & Kim, M. (2024). It is like a friend to me: Critical usage of automated feedback systems by self-regulating English learners in higher education. Australasian Journal of Educational Technology, 40(1), 1–18. https://doi.org/10.14742/ajet.8821
15. Ma, Q., & Chiu, M. M. (2024). Self-regulated and collaborative personalised vocabulary learning approach in MALL. Language Learning & Technology, 28(1), 1–27. https://doi.org/10.64152/10125/73579
16. Mukherjee, A., & Singh, S. (2026). Leveraging AI chatbots for self-directed learning: A study of practices and drivers to adoption among college students. Turkish Online Journal of Distance Education, 27(1), 70–81. https://doi.org/10.17718/tojde.1632775
17. Muslihati, Zen, E. F., Hambali, I. M., Ashar, M., Saputra, N. M. A., & Kurniawan, N. A. (2022). Investigating needs of academic support using personalized learning system to enhance academic success among fresh year student. In 2022 2nd International Conference on Information Technology and Education (ICIT&E) (pp. 363–367). IEEE. https://doi.org/10.1109/ICITE54466.2022.9759842
18. Omirali, A., Kozhakhmet, K., & Zhumaliyeva, R. (2025). Digital trust in transition: Student perceptions of AI-enhanced learning for sustainable educational futures. Sustainability, 17(17), 7567. https://doi.org/10.3390/su17177567
19. Peters, M. D. J., Marnie, C., Tricco, A. C., Pollock, D., Munn, Z., Alexander, L., McInerney, P., Godfrey, C. M., & Khalil, H. (2020). Updated methodological guidance for the conduct of scoping reviews. JBI Evidence Synthesis, 18(10), 2119–2126. https://doi.org/10.11124/JBIES-20-00167
20. Poznanskyy, R., Pryimak, L., Apelt, H., Savchuk, N., & Kopchak, L. (2025). Transforming foreign language education: The role of AI-based adaptive learning systems in enhancing personalized learning amid global instability. Metaverse Basic and Applied Research, 4, 179. https://doi.org/10.56294/mr2025179
21. Rakhmetov, M., Sissenova, A., Moldasheva, R., Dautkulova, A., Uteuliyeva, K., & Orazbayeva, B. (2026). Methodological foundations of AI-driven distance learning platforms: Evidence from learning analytics and structural equation modeling. Journal of Theoretical and Applied Information Technology, 104(8), 154–163.
22. Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. Technology, Knowledge and Learning, 22(3), 317–333. https://doi.org/10.1007/s10758-017-9316-1
23. Shamsudin, M. F., & Cao, L. (2025). Investigating the mediating role of student engagement in the relationship between machine learning-enabled personalized learning and academic performance. In

Proceedings of the 2nd Guangdong-Hong Kong-Macao Greater Bay Area Education Digitalization and Computer Science International Conference (EDCS 2025) (pp. 74–82). Association for Computing Machinery. https://doi.org/10.1145/3746469.3746483

24. Shermanova, F., & Taylakova, G. (2026). Pedagogical and methodological capabilities of artificial intelligence tools in developing digital literacy. Proceedings of the International Conference on Applied Innovation in IT, 14(2), 351–357. https://doi.org/10.25673/123946
25. Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., . . . Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. Annals of Internal Medicine, 169(7), 467–473. https://doi.org/10.7326/M18-0850
26. Waldrip, B., Cox, P., Deed, C., Dorman, J., Edwards, D., Farrelly, C., Keeffe, M., Lovejoy, V., Mow, L., Prain, V., Sellings, P., & Yager, Z. (2014). Student perceptions of personalised learning: Development and validation of a questionnaire with regional secondary students. Learning Environments Research, 17(3), 355–370. https://doi.org/10.1007/s10984-014-9163-0
27. Zhang, Z., & Yang, R. (2025). Personalised language learning through technology: Examining how digital literacy shapes proficiency and communication strategies. Journal of Computer Assisted Learning, 41(4), e70069. https://doi.org/10.1111/jcal.70069