ONLINE LEARNING
Volume 30, Issue SI2 (2026) · e5641
https://doi.org/10.24059/olj.v30iSI2.5641

Who is AI supporting? A systematic review of AI-enabled learner support in higher education

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Abstract

Learner support is a cornerstone of open, distance, and digital education (ODDE), yet providing effective, scalable, and equitable support remains a persistent challenge. With the rise of artificial intelligence (AI) and increasing publications on it, it is important to see how higher education institutions are adopting AI-enabled tools to support their learners. This study systematically reviewed and synthesized 61 publications to examine how AI has been applied to learner support, what practices and constraints are reported, and whether current approaches meet diverse learner needs. The included studies, identified without applying time restrictions, span publications from 2010 to 2025. Using the Inclusive Support for Student Persistence Model (ISSPM) and an AI typology, the review finds that adaptive systems and personalization, particularly chatbots and recommender systems, are the most common applications, followed by profiling and prediction. Reported benefits include timely interventions, personalized guidance, and workload reduction for staff; however, technical limitations, privacy concerns, limited inclusivity, and reduced human interaction pose significant challenges. The review finds critical blind spots, especially in addressing diverse learner needs and in the underexplored transition phase of the student journey. Notably, diversity in population, such as marginalized groups or neurodivergent learners, was absent. By offering a structured synthesis from an institutional perspective, this review contributes to the established learner support research about the role of AI in shaping equitable and sustainable learner support in digital higher education.

Keywords: Learner support, Artificial intelligence, Student services, Digital education, Online education, Distance education, diversity

Introduction

Learner support is essential for learner success, retention, and a well-rounded learning experience (Moore & Kearsley, 2012; Rotar, 2022a; Simpson, 2004, 2013), particularly when the learner is detached from the time and space of instruction (Brindley, 2014). Open and distance education (ODE), in this sense, has long faced low student retention rates, and academic support interventions have continued to be one of the major concerns of the field (Cefa & Zawacki-Richter, 2025; Zawacki-Richter & Bozkurt, 2023). Learner support has been critical for learner success in distance education (Brindley & Paul, 1996; Moore & Kearsley, 2012), especially for learners getting engaged with online learning (Rumble, 2000). The flexibility and independence in time and place of open and distance learning are widely adopted by conventional higher education institutions, but in more digital settings to reach out to their students (Xiao, 2018). This shift accelerated during the global emergency remote teaching (ERT) period (Bozkurt & Sharma, 2020; Hodges et al., 2020), when institutions worldwide moved online, often without preparation. Conventional universities were suddenly immersed in ODE challenges. The widely enabled online practices and digitally enhanced setting also in conventional universities brought a new term encapsulating all forms of HE as defined by Zawacki-Richter and Jung (2023), as an umbrella term: open, distance, and digital education (ODDE), encompassing digitally enhanced education also in conventional education, including technology-enhanced learning or blended learning, laying their roots in ODE practices.

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The expansion of ODE in the 1990s spurred more research on student support due to quality problems that emerged with the growth of distance teaching institutions (Zawacki-Richter & Naidu, 2016). In the 2010s, with the rise of artificial intelligence (AI) and big data, attention turned to intelligent support systems (ITS) (Zawacki-Richter & Bozkurt, 2022). The expansion of access to higher education and the increasing digitalization of learning, first through ERT, then through ongoing technological advances, have made ODDE a reality for almost all universities (Arnhold & Bassett, 2021). Yet, despite its flexibility, ODDE demands strong motivation, self-regulation, time and task management, goal orientation, and the ability to work independently and collaboratively (Brindley, 2014). Learner support in ODDE will therefore remain crucial for helping students succeed, whether in technology-enhanced classrooms or fully online environments.

Providing effective learner support at scale is challenging for ODDE institutions serving geographically dispersed and diverse populations (Daniel et al., 2009). It requires careful cost analysis, substantial administrative resources, robust systems (Rumble, 2000), although it might prove more cost-effective for the university in the long term (Burke, 2019; Simpson, 2023). To streamline these support processes, the advent of the Internet played a key role (Rotar, 2022b) in enabling more personalized and automated support mechanisms (Dollinger et al., 2020; Walsh et al., 2020) alongside broader communication paths to be utilized (Zawacki-Richter & Anderson, 2014).

More recently, the techno-feudal rise of big tech companies making generative artificial intelligence (GAI) publicly accessible at scale fueled new learner support possibilities despite criticism (Cefa et al., 2025). Already, California State University system proudly announced integrating ChatGPT Edu across 23 campuses, serving over 460,000 students and 63,000 faculty at no cost with the promise of offering personalized tutoring, study guidance, and research help (DiPierro, 2025).

At this stage, we aim to critically explore the state-of-the-art in higher education learner support systems and pinpoint the AI-powered support interventions being applied or designed to help learners by means of a systematic literature review. Therefore, this study addresses the following research questions:

RQ 1: What is the scope of research on AI use in higher education for learner support?

RQ 2: What practical experiences and constraints are documented in the literature?

RQ 3: To what extent do current AI-driven learner support services address the diverse needs of learners?

Notably, no directly comparable systematic reviews focusing specifically on AI-enabled learner support in higher education were identified through our search strategy, highlighting a significant gap in the literature and the need for a structured synthesis of this emerging field. By this review, we do not only demonstrate the current institution-based systemic AI applications and their functions in learner support according to the learner journey, but also critically engage with the homogeneity of learner profiles in the datafication process.

Conceptual Framework and Literature Review

Learner Support in ODDE

Learner support is recognized as an institutional dimension (Cefa & Zawacki-Richter, 2025) defined through the relationship between the institution and the learner. Consequently, the responsibility of higher education institutions is to delineate the areas of "service" provided to students. Tait (2000) conceptualizes three interrelated dimensions: cognitive, affective, and systemic activities. Cognitive support focuses on facilitating students' mastery of course content and the development of academic skills; affective support addresses the emotional and motivational aspects of learning; and systemic support encompasses administrative, technical, and organizational processes. Accordingly, "the main institutional systems involved in learner support are teaching and tutoring, advising and counselling, and information and administrative" (Brindley et al., 2004, p. 13). Building on this conceptualization, this study adopts the definition by Cefa (2025):

> […] The learner support ecosystem constitutes communication that allows learners to self-direct, find guidance, connect and build a network, and engage with resources (human or inhuman) across cognitive, affective, and systemic domains, while pursuing diversity, inclusivity, and mitigating the historical education divide (p. 12).

To achieve this, the timing of the support intervention matters. Thorpe (2003) distinguishes support before, during, and after learning; Simpson (2013) differentiates reactive (after difficulties emerge) and proactive (before disengagement) approaches. As with most sociological structures, it is challenging to divide multifaceted systems into clearly separated layers. Tait (2000) highlights six design factors: student characteristics, programme demands, geography, technology, scale, and management. Simpson (2002) separates academic (course mastery, feedback, learning skills, enrichment) from non-academic (advising, practical help, advocacy, administration) support. Floyd and Casey-Powell's (2004) Inclusive Student Services Process Model (ISSPM), developed for online education, aligns support with five phases of the learner journey:

(1) Learner intake: initial recruitment, orientation, and preparation for study;
(2) Learner intervention: targeted actions to address emerging academic or non-academic issues;
(3) Learner support: ongoing assistance, both academic and administrative, throughout the study period;
(4) Learner transition: guidance for progression, completion, or movement to further study or employment; and
(5) Measurement: systematic evaluation of support effectiveness to inform continuous improvement. By structuring interventions along this timeline, the model enables institutions to plan proactive and integrated support strategies that respond to students' evolving needs.

Rotar (2022a), using the ISSPM as a framework for her systematic review on the effectiveness of online academic student support, emphasizes its usefulness as the model outlines the key tasks associated with each stage of the student learning journey.

Before addressing the methodology of this study, the following section will first provide a conceptual overview of the significance and scope of learner support in ODDE, with particular attention to emerging AI applications.

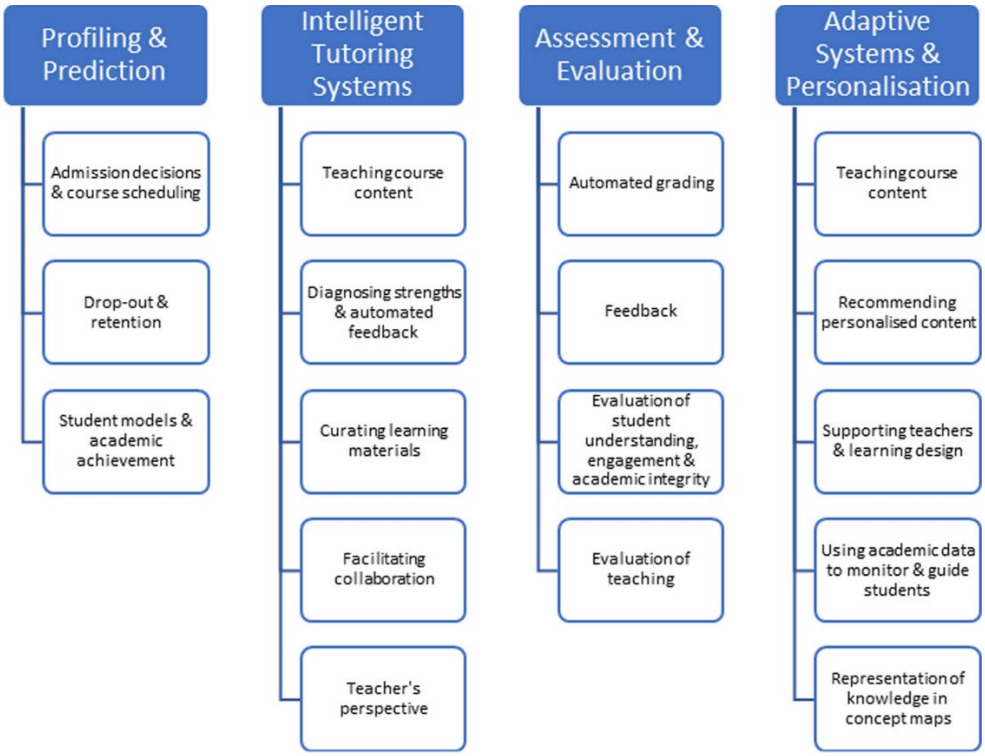
AI in Education (AIEd) and Learner Support

The application of AI for learner support is not a recent development; its roots extend back several decades, with early systems exploring automation in tutoring. The first ITS reported was the SCHOLAR system, launched in 1970, which allowed the reciprocal exchange of questions between teacher and student, but did not hold a continuous conversation (Welham, 2008). However, the growing availability of computing power, data, and advances in machine learning have expanded the scope and precision of such interventions, prompting renewed examination of their role in supporting students.

AI is a complex theme with a lot of technicalities. To keep the focus on learning and education rather than technical developments, the literature is discussed under the typology developed by Zawacki-Richter et al. (2019), with more recent developments in large language models (LLMs) located within the fourth area, 'adaptive systems and personalization' (Figure 1).

Figure 1

AIEd typology by Zawacki-Richter et al. (2019), visualized by Bond et al. (2024, p. 4)



Profiling and prediction encompass predictive models that use student data to predict and profile students on their performance, prospective program completion rates, and time; more importantly, the risk of dropping out (Jayaprakash et al., 2014). With the advancement of AI as well as the wide usage of LMS, especially in ODDE, a variety of student data became available, which opened the path for learning analytics (Joksimović et al., 2015; Siemens, 2013). Despite the long history of prediction-based analysis, it was not in use in education until 2010 (Joksimović et al., 2019). Learning analytics is defined as "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long & Siemens, 2011, p. 34). Through advanced computational techniques such as Bayesian modelling, cluster analysis, and predictive learning analytics (Herodotou et al., 2019), institutions provide learner support (Joksimović et al., 2019) with early prediction of students' course or program completion and academic performance (Calvert, 2014; Gašević et al.,

2015; Tempelaar et al., 2021). The predictive power enables institutions to optimize learning (Macfadyen & Dawson, 2010), and identify patterns that should lead to taking proactive action to change the pattern (Duval, 2011), as well as personalize the learning process (Chatti et al., 2012).

ITS are pedagogically designed non-human tutoring systems that deliver domain-specific information with step-by-step guidance. Huang and Chen (2016, p. 341) outline several models commonly incorporated into ITS: the student model, which contains information on the learner's knowledge level, e.g. cognitive abilities or motivation; the teacher model, which analyzes students' current status, selects suitable teaching strategies and methods, and offers help and guidance; and the domain model, which represents the knowledge held by both students and teachers; and the diagnosis model, which evaluates errors and deficiencies based on the domain model.

Assessment and evaluation are fields largely focus on teaching and learning processes, mostly focusing on feedback, automated assessment, or teaching evaluation (Bai et al., 2022; Zawacki-Richter et al., 2019). This category utilizes mostly training models through various algorithms such as supervised learning.

Adaptive systems and personalization, the fourth category, is another broad term without an agreed definition. The educational activities compose creation of personal content, recommender systems, monitoring and guidance during learning. Within this study, chatbots were also taken under this category with particular reference to its function in support systems. Actually, starting from the 1950s, continuing with ELIZA in 1966 by Weizenbaum (Han & Lee, 2022), chatbots has long been the most well-known tool of adaptive systems. The emergence of generative AI in the public domain, particularly through widely accessible chatbot interfaces, has sparked significant interest across various fields, including education, with the hope that there is a system capable of supporting learning, providing personalized content, and delivering timely feedback (Cefa et al., 2025; Jensen et al., 2024; Lo, 2023). Chatbots, however, vary in their underlying architectures, interaction styles, and capacities for adaptation, ranging from rule-based dialogue systems to large-scale, transformer-based generative models (Arun et al., 2019; Suta et al., 2020). These differences influence not only the quality and accuracy of responses but also the degree to which the systems can tailor interactions to individual learner needs, adapt to contextual cues, and maintain pedagogical coherence over time. As such, understanding the spectrum of chatbot capabilities is crucial for evaluating their educational potential and for aligning their use with instructional goals and ethical considerations.

By rigorously compiling the state of the art in the literature on AI-enabled learner support, this review seeks to offer an evidence-based account of the current landscape in both research and practice. In doing so, it examines not only areas of promise but also blind spots and specific domains, including approaches to the preservation of pedagogical integrity and data privacy.

Methods

Research Method

This study employed a systematic review to provide an overview of the literature on learner support at the institutional level that leverages AI. Systematic reviews are widely recognized as a preferred methodology in ODDE, particularly in light of the rapid growth in publications in the field, especially concerning AI (Bond et al., 2024; Zawacki-Richter et al., 2025). Their methodological rigor lies in the use of replicable and reproducible procedures, implemented through a series of predefined steps (Buntins et al., 2023; Gough et al., 2017; Zawacki-Richter et al., 2025), enabling the results to inform evidence-based discussions. The following sections present a detailed account of the

procedure, which is fully documented in the review protocol published on the Open Science Framework (OSF) platform (see: https://osf.io/cpwdz).

Data curation and criteria setting

In the initial phase of the study, the Population, Intervention, Comparison, and Outcome (PICO) (Page et al., 2021) framework was established to define the research scope, as outlined in the introduction. Based on this framework, the initial search string was developed and iteratively refined by incorporating alternative synonyms for "learner support" and adjusting the scope of AI applications (Table 1).

Table 1

Final search string

Topic	Search string
Study focus	("student support" OR "learner support" OR "student service" OR "learner service" OR "support intervention" OR "academic services")
	AND
Intervention	("artificial intelligence" OR "AI-driven" OR "AI-powered" OR "generative AI" OR intelligent OR virtual OR smart OR "recommender system" OR "recommendation system" OR personalized OR adaptive OR automated OR chatbot OR "reinforcement learning" OR "learning analytics" OR predictive)
	AND
Education level	("higher education" OR university OR college OR post-secondary OR "tertiary education" OR "vocational education")

The exclusion and inclusion criteria were set (Table 2) based on the research questions. Despite AI's relatively long history and review studies on particular AI applications for particular purposes (e.g., Labadze et al., 2023; Larrabee Sønderlund, 2019), there is no overview of the various uses of AI in student support in higher education. Therefore, no time restrictions were applied, ensuring the inclusion of all relevant studies. Although analytics and algorithm development studies were included, studies that use synthetic data were excluded as they do not include real student data and remain purely technical for the research questions this study seeks to answer.

Only peer-reviewed journal articles and papers in conference proceedings were included, while books, editorials, and other forms of grey literature were excluded to ensure a consistent methodological comparability across peer-reviewed studies in an exponentially increasing trend of paper production on AI.

Table 2

Inclusion and exclusion criteria

Criteria	Inclusion	Exclusion
Time	No limit	-
Education setting	Higher education	Early childhood education, K-12, non-formal education, informal education
Intervention	AI-powered, non-human mediated support (including analytics, predictive models)	No AI-powered support OR support is not the purpose for the use or development of AI
	Applicable by the institution and not subject-domain specific.	Support is a secondary topic in the application.
Document type	Journals, conference proceedings	Books, dissertations, booklets, reports, editorials, commentaries, letters
Language	English	Not in English

Both learner support and AI have blurred lines as they are multi-faceted phenomena. If the intervention was not applicable at an institutional level but course-specific on the micro level of learning and teaching, these studies were excluded.

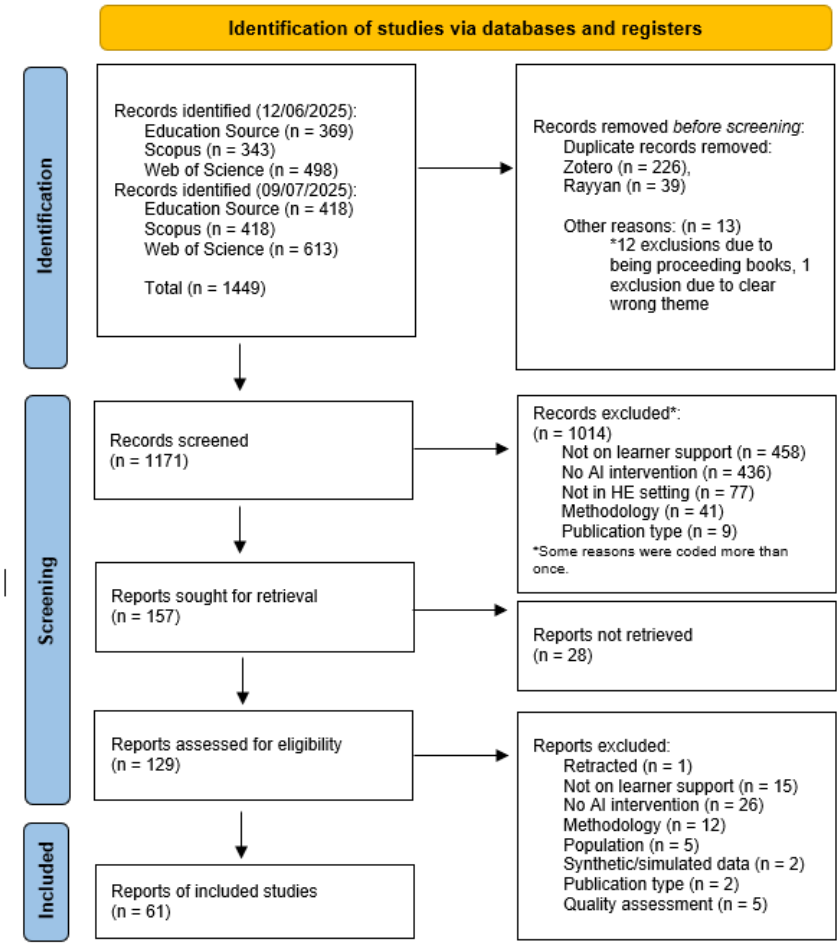
Screening and coding process

The final search was conducted on June 12, 2025, in three databases: Education Source, Scopus, and Web of Science (WoS). They were selected to ensure wide coverage of education research. Together, these databases are widely recognized as providing broad and complementary indexing of peer-reviewed literature relevant to higher education and educational technology.

On July 9, the additional search term “predictive” was introduced, and the search was repeated across the same databases. Language and document-type filters were applied in all three databases, and to ensure consistency with Scopus and WoS, the Education Source search was restricted to “peer-reviewed” publications only. As the PRISMA flow chart displays in Figure 2, out of 1449 articles identified, the phases of duplicate cleaning, title and abstract screening, and full text screening were followed, finally forming a corpus of 61 included studies.

Figure 2

PRISMA flow diagram (adapted from Page et al., 2021)



The initial search results were imported into the reference management system Zotero for preliminary duplicate removal. For title and abstract screening, 1,212 references were uploaded to the systematic review software Rayyan. Additional duplicates were identified using the software's automated detection feature, set to a 0.90 resemblance threshold, which found and merged 39 further duplicates.

Two rounds of blind title and abstract screening were conducted by the first and second authors, with reconciliation meetings to resolve discrepancies. This process yielded a Cohen's kappa (Cohen, 1960) value of 0.80, indicating substantial interrater reliability. For full-text screening, the same blind screening process was applied, necessitating two rounds for reconciliation and resulting in excellent agreement between two reviewers (Round 1: $\kappa = 0.70$; Round 2: $\kappa = 1.00$).

Data extraction and coding were conducted using EPPI-Reviewer Web (https://eppi.ioe.ac.uk/EPPIReviewer-Web/home), a dedicated tool for systematic reviews. The review focused on two complex, multi-dimensional phenomena: learner support and AI. Each topic required careful categorization due to its diverse and layered nature.

Given the scope of the systematic review, which involved analyzing dozens of studies with varying purposes, methodologies, and theoretical frameworks, it was essential to adopt a robust and

reliable approach to data interpretation. The coding process was deductive, shaped by two relevant theoretical models to ensure coherence and depth in the synthesis. This approach ensured that the extracted data would be both meaningful and easily transferable.

For the learner support interventions, the ISSPM by Floyd and Casey-Powell (2004) was adopted. This model includes five stages of institutional support aligned with the student learning journey, from initial enrollment to graduation (see Section 1). The sub-codes were adapted where necessary to describe the study's content.

For the AI dimension, the typology proposed by Zawacki-Richter et al. (2019) was used. This framework categorizes AI applications in education into four broad areas (see Figure 1), with subcodes adapted to suit the context of the reviewed studies. AI terminology often varies significantly across disciplines, making a unified classification challenging; the use of this typology helped to standardize the analysis despite such variability.

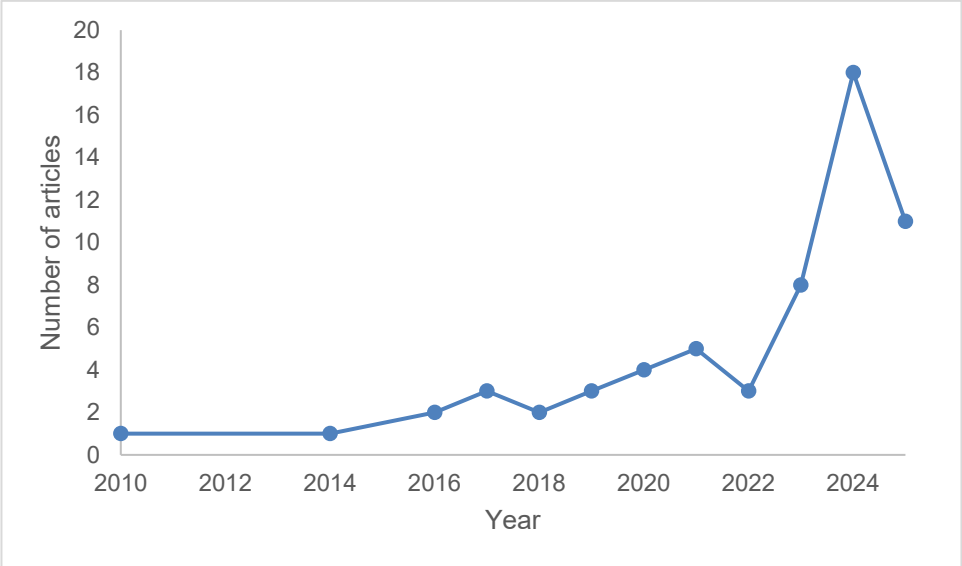
Study and data characteristics of the corpus

Disciplinary distribution of the studies in the corpus, categorized according to the OECD Field of Science and Technology (FOS) classification, shows a predominance of works in the Natural Sciences (n = 29), followed by the Social Sciences (n = 15). A smaller number of contributions came from Engineering & Technology (n = 9), Medical & Health Sciences (n = 1), Humanities & Arts (n = 1), and other fields (n = 5), which are administrative support divisions of universities, with two studies not being traced back to the disciplinary affiliation. Within the Social Sciences, most studies were classified under Educational Sciences (n = 10). In the Natural Sciences, the largest share fell under Computer and Information Sciences (n = 27), followed by Mathematics (n = 4) and other Natural Sciences (n = 1).

Although no time limit was set, the earliest publication in the corpus dates back to 2010 only and follows a steep curve in the last three years (Figure 3).

Figure 3

*Publication trend according to years (N = 61) *



To encompass a wide range of perspectives, the corpus included studies that either implemented AI-driven learner support or developed AI models for such support. Methodologically, these were coded as either Technical/Algorithm-focused (n = 20) or Intervention/Educational (n = 38), with three studies spanning both categories. If the study technically engaged in the development process, these studies were coded as technical papers. However, the studies that describe the intervention model with a practical focus were coded under intervention studies. The details are given in Table 3.

Table 3

Detailed description of technical / algorithm-focused studies

Data source	n
Institutional records	16
LMS Data	6
Participants from institutions	5
Public open dataset	4
Commercial products	2
Not specified	3

The technical or methodological papers dominantly source data from institutional records. The four studies that did not specify the data source, specified that they used institutional historical data, but as the records were not collected for the study and details are unclear, they were coded as N/S.

Consent statements for data sources were reported in only six studies (27.3%) (e.g., Acang et al., 2023; Ajoodha et al., 2020; Balderas et al., 2023; Bhave et al., 2024; Channarukul et al., 2017; Gray & Perkins, 2019; Hill et al., 2025). This code did not apply to two studies since they used a public data set.

Table 4

Methodological approach of Intervention / Educational Studies

Sub-subcategory	n
Intervention / Model description	13
Qualitative	3
Quantitative	14
Mixed method	12

Almost one third (n = 13) of the Intervention/Educational studies category (n = 41) came from intervention/model description papers. The empirical papers were predominantly quantitative or mixed-methods studies. Of the quantitative studies, two tested the model and were consequently coded under both the *intervention* and *quantitative* categories. Only three studies employed a qualitative design.

Across the corpus, the primary population group was students (n = 55), representing the dominant focus of AI-driven learner support research. Smaller shares focused on faculty members (n = 7) and administrative staff (n = 5). Four studies did not specify a participant group as they described the developed product without user data. The “Other” category (n = 2) encompassed studies that used developers as their data source (e.g., Garcia et al., 2023; Gonçalves et al., 2022).

Finally, the distribution of the corpus by educational setting was heavily weighted toward conventional campus-based institutions (n = 41, 67.2%), followed by open and distance education institutions (n = 13, 21.3%) and dual-mode universities (n = 3, 4.9%). In four cases (6.6%), the institutional type could not be identified.

Limitations

Every study is inevitably shaped, thus limited by the methodological and contextual choices it makes. This research is limited to English-language publications, which inherently restricts the representation of scholarly work produced in other languages. As a result, insights from non-English speaking contexts, particularly from countries with robust traditions in open and distance education, may be underrepresented. Given that learner support is mostly handled as a meso-level, namely, an administrative matter, related research might frequently be published in national or regional journals in the home language.

The exclusion of dissertations and other forms of grey literature may have introduced publication bias, as studies reporting non-significant, exploratory, or critical findings are less likely to appear in peer-reviewed journals, a potential limit to the comprehensiveness of the corpus.

Moreover, the scope of the study is confined to three academic databases. While each of these platforms is recognized for its credibility and wide coverage, the selection inevitably introduces some degree of bias. In parallel to that, more critical voices are more likely to prefer publishing in books, edited volumes, and blogs. Relevant literature published in less prominent or region-specific journals as well as other publication areas are excluded.

Finally, no formal quality assessment of the included studies was conducted. Nevertheless, studies lacking a clearly described methodology were excluded during full-text screening to ensure a minimum level of methodological transparency.

Results

RQ 1: What is the scope of research on AI use in higher education for learner support?

In line with the ISSPM model's five phases of learner support, this study examined how AI technologies were applied across these phases. The findings indicate that AI use was most prominent in the Learner Support Phase, followed by the Measurement, Learner Intake, and Learner Intervention phases. No AI-driven interventions were identified in the Learner Transition Phase. For an overview and meaningful interpretation in the following sections, Table 5 displays the cross-tabulation of the AI intervention with five learner support phases.

Table 5

Co-occurences of AI-driven intervention and support phases

AI intervention/Support Phase	Intake	Intervention	Support	Transition	Measurement
Profiling & prediction	1	-	9	-	20
Assessment & evaluation	-	-	1	-	-
Adaptive systems & personalization	12	14	14	-	-
Intelligent tutoring systems	-	-	1	-	-

Table 5 depicts the weighted use of AI-driven interventions in the Learner Support and Measurement Phases. As one tool might be used in the same paper for more than one service, Table 6 shows the total uses of the subcategory of AI typology.

Table 6

Frequency of AI applications for learner support

Code	Count
Adaptive systems & personalization	41
Profiling & prediction	30
Intelligent tutoring systems	1
Assessment & evaluation	1

As Table 6 shows, the most frequent uses are in adaptive systems & personalization, closely followed by profiling and predictions. In the following subsections, we examine how each subfield of the AI typology was applied across the corpus, following the learner's journey from the Intake phase to the Measurement phase.

Adaptive systems & personalization (AS&P) in learner support phases

AS&P is the most used type in learner support phases, all in the first three phases (Table 7).

Table 7

Co-occurrences of AS&P uses in learner support phases

Codes	Intake	Intervention	Support	Transition	Measurement
Chatbots-LLM-NLP	7	11	8	-	-
Recommending personalized content/program	3	1	4	-	-
Monitor & guidance	1	1	3	-	-
Robots	-	1	-	-	-
VR, Simulations (AI-based)	1	-	1	-	-

As the table presents, the most frequently used AI technology is chatbot, followed by recommender systems, and a few examples of monitoring, robots and VR.

The Learner Intake Phase benefited from AS&P, via chatbots for homepage support (n = 3; e.g., Abdul Razak, 2024; Prasertsri et al., 2024; Sereni, 2024), admissions/registrations (n = 2; e.g. Pansombut & Kirimasthong, 2025; Thongda & Songpan, 2023), and financial aid information (n = 1; e.g., Nurshatayeva et al., 2021).

Orientation is one of the key services in the Learner Intake Phase, and this includes physical and cognitive orientation of the learner in the system as well. For campus orientation, Garcia et al. (2024) initiated a virtual tour connected to the metaverse system of FEU Institute of Technology in the Philippines during the pandemic. Sereni (2024) demonstrated an effective example of an integrated international support service structure (advisory, social programs, communications) in Australia. They utilized a self-guided campus tour via a scripted chatbot to make the tours scalable and accessible. During orientation week, students log into the "Fantastic Race" app with their Uni ID, join a randomized team and complete location-based challenges. The app itself was assembled with Power Apps (interface), Power Automate (flows to SharePoint), and Excel (scores). Drawing on Copilot, the

team generates the step-by-step wiring instructions that made these pieces talk to each other smoothly. Data is secured in SharePoint; rankings update automatically; access is Uni-login only. Over 600 students have participated since its Semester 2, 2023 launch, with very positive feedback. Another chatbot was utilized as a cognitive agent, called "BARICA" at the University of Zagreb in Croatia to provide information in English on faculty location, working hours of the personnel, schedules, particularly aiming first year students (Schatten et al., 2021).

In this respect, the initial information provision is the homepage of a university. As the initial point of contact between the institution and students, the website can sometimes be confusing for newcomers or may lack essential information. For cognitive orientation, chatbots (n = 4; e.g. Abdul et al., 2024; Nurshatayeva et al., 2021; Sereni, 2024), recommendation systems (n = 1; Acang et al., 2023) and AI-based VR (n = 1; Garcia et al., 2023) were used to provide orientation and guidance via the institutional website.

Similarly, Prasertsri et al. (2024) implemented a frequently asked questions answered by a chatbot via LINE OA to avoid answering repetitive questions without contacting the university departments in Thailand. The users have to use the LINE application with their accounts. Two components: (1) a Dialogflow-based NLP chatbot; (2) LINE "Rich menu" shortcuts for direct access to services. Users add the faculty's LINE OA, receive a welcome message, and can either chat (free-text) or tap Rich-menu shortcuts to reach external resources (faculty website pages, social media, downloadable forms, Google Maps, complaint portal). Dialogflow provides intent modeling, language understanding, memory of key terms, and continual improvement via machine learning; the chatbot supports bi-directional conversation and responds with text, images, and links. Another chatbot was developed by Abdul et al. (2024) using NLP and ANN trained on JSON dataset with 80 % accuracy to increase the accessibility to information by students with immediate responses, thus avoiding workload on support.

A further service in Intake phase was financial aid. It is a key factor contributing to the 14% summer melt rate among U.S. college-intending high school graduates, alongside other overwhelming pre-enrollment tasks such as financial aid paperwork, placement tests, and course registration (Nurshatayeva et al., 2021). Without adequate family support or sufficient financial resources, these processes become even more challenging. Nurshatayeva et al. (2021) evaluated the "PeeDee" chatbot at East Carolina University, which sent tailored reminders, provided information, and answered questions in real time to all ECU-intending students. While the overall outreach increased student loan acceptance by 4 %, further analysis showed that first-generation students, who began with low initial completion rates for pre-matriculation tasks, experienced more gains (See RQ3 for more details).

A course registration recommender model was developed to "[…] profile the strengths of the education providers and the possible programs that students will endure" (Acang et al., 2023, p. 2). Thus, students were aimed to be placed the learners on the right course.

In the **Learner Intervention** phase, institutions primarily deployed chatbots as help-desk tools for administrative queries. Development of chatbots centered on applications and models aimed at reducing support-staff workload, indicating a need from technology to cater students at scale. Examples include the LA-K Telegram chatbot (Cahyana et al., 2024); a K-NN–based classification chatbot introduced as an alternative to WhatsApp exchanges between students and desk support (Hardi et al., 2022); a chatbot built with the ChatterBot library to reduce response delays in online learner-support systems (Ndunagu et al., 2025); an LLM-based chatbot to help academic advisors for extracting frequently asked questions (Wangwiwattana & Jantarick, 2024)

Öncü and Süral (2024), for instance, examined user perceptions of Anadolu University's Virtual Assistant using a sequential explanatory mixed-methods design. The keyword-based assistant, a rule-based chatbot, matched incoming queries to likely answers about administrative questions such as enrollment, tuition, course information, and related student-affairs topics. Although participants expected greater functionality (e.g., full answers rather than redirects), overall ratings for usability, information quality/security, and design were positive. Learners also expressed a desire for stronger academic-support features.

A further study, exploring GenAI for learner support, compared Anadolu University's rule-based assistant with GenAI chatbots (ChatGPT-3.5 and Bing Copilot) across four scenarios (Öncü et al., 2025). When provided with FAQs and their answers, ChatGPT-3.5 correctly matched 95.48% of previously unanswered learner questions, but its accuracy dropped to 54.24% when asked to generate full responses directly from that dataset; by contrast, Copilot, drawing on the open web without the FAQ corpus, answered learner questions correctly 64.97% of the time. The authors recommended hybrid arrangements: keep a vetted, rule-based layer for authoritative answers, use GenAI for intent recognition/matching, and escalate to human experts when needed. Priccilia and Girsang (2024) reached a similar conclusion with a GPT-2–based chatbot: for narrow, templated student-service tasks, a generative model isn't the best choice. It's more defensible when the scope is broader, and accuracy can be improved by exploring additional data-augmentation strategies.

A different intervention utilized the hybrid structure on student success strategies via a low-tool-required open-source Robotic Study Companion (RSC). (Baksh et al., 2024). The RSC provides subject-specific interaction without performance scoring, adjusts to each learner with customized study plans, and can process spoken commands through an open-source Python speech-recognition library and the GPT-3 API.

In the **Learner Support Phase**, several studies applied chatbots for academic advising (n = 3; e.g., Lucien et al., 2024; Lytridis & Tsinakos, 2025; Sweidan et al., 2021), instructional assistance, and tutoring. Advising chatbots were designed to answer course planning queries and recommend schedules aligned with institutional policies, showing promise in streamlining decision-making for students with varied academic standing (Sweidan et al., 2021). Other work explored socially aware recommendations that integrate peer network information into course scheduling, reducing search time and supporting students' preference to enroll alongside friends (Channarukul et al., 2017).

AI-based course assistants have also been deployed to provide continuous learning support in online environments. In a study of a commercial system in the United States, such assistants were associated with higher GPA and gains in motivation and self-efficacy (Hanshaw et al., 2024). Another related research examined adaptive courseware that diagnoses learner progress and personalizes instructional pathways, showing improved pass rates and modest learning gains (Ford et al., 2017). Beyond individual support, adaptive prompts in collaborative learning environments improved task efficiency and learning outcomes compared to fixed guidance, suggesting benefits of real-time, targeted support during peer interaction (Karakostas & Demetriadis, 2014).

A small set of studies addressed mental well-being (n = 3; Alves-Noreña et al., 2025; Balderas et al., 2023; Bhave et al., 2024). These interventions include conversational agents to monitor emotional states (Alves-Noreña et al., 2025); initial support through chatbots (Balderas et al., 2023) and identifying risk behaviors and providing a point of contact between students and counseling services, particularly when staff availability is limited (Bhave et al., 2024).

Prediction & Profiling (P&P) in learner support phases

Learner support and measurement phases utilized the P&P most (Table 8), which is logical as these are the phases that allow institutions to leverage secondary data and LMS data to measure and run profiling and prediction models.

Table 8

Co-occurrences of P&P uses in learner support phases

Codes	Learner Intake	Learner Intervention	Learner Support	Learner Transition	Measurement
Drop-out & retention	1		2		11
Student performance			5		7
Course scheduling			1		
student profiles, characteristics			1		2
EWS			2		2

The Learner Intake Phase one study applied prediction and personalization (P&P) to support early detection of at-risk students. Ajoodha et al. (2020) trained a classifier to estimate student risk profiles at entry using pre-tertiary academic records and personal background data, enabling proactive support for expanding first-year cohorts in South Africa.

In the Learner Support Phase, P&P was widely used for retention and performance monitoring through learning analytics (e.g., Herodotou et al., 2020; Roestenburg et al., 2024). Herodotou et al. (2020) used predictive analytics in a randomized trial to target motivational outreach to at-risk students, improving retention by allocating intervention efforts to those most likely to benefit. Similar applications linked early warning systems to instructional support and tutoring (Khan et al., 2025), or delivered digital nudges that increased persistence among vulnerable first-year students (Rodríguez et al., 2022). Khan et al. (2025) reported five cases from Saudi universities where a predictive analytics platform enabled early retention interventions by providing instructional support and tutoring. Similarly, Rodríguez et al. (2022) implemented a nudging system for first-year students at risk of failure or dropout, which significantly improved retention by enhancing students' sense of guidance and support.

Several studies also highlighted the role of analytics in informing educators. At the Open University, weekly risk predictions guided instructors toward students unlikely to submit the next assignment (Herodotou et al., 2019), while Honson et al. (2024) reported that early alerts reduced barriers to timely instructor outreach. Analytics also supported academic counselling through tools providing transparent program and grade information, improving decision-making about course loads (Henriquez et al., 2024). Extensions to library services showed that integrating resource-usage data into institutional dashboards correlated with higher academic performance (Jantti & Heath, 2016).

One study applied P&P to well-being. Thesen (2025) clustered self-reported data from U.S. medical students to identify anxiety and depression risk groups, showing the potential of unsupervised models for directing students to support services.

Measurement, unsurprisingly, was the most common phase for P&P use. Research across phases focused on predicting retention and dropout (e.g., Ajoodha et al., 2020; Herodotou et al., 2020). Villano et al. (2018) found that student inactivity was the strongest predictor of withdrawal and that early alert systems were most accurate during the first year. Additional models have used machine

learning to identify factors affecting persistence in specific disciplinary contexts—such as medicine (Hammoudi, 2023), computer science (Li et al., 2024), and non-traditional student populations (Seo et al., 2024)—often achieving high accuracy in predicting degree completion timelines (Ndou et al., 2021).

Assessment & Evaluation (A&E) in learner support phases

Only one A&E study fell within the Learner Support phase, focusing on academic advising and performance-relevant feedback (Khumalo et al., 2023). They investigated the AutoScholar Advisor System (Auto-Ad) for student advising and giving feedback on how they perform in a South African university. The Auto-Ad is "designed to automate and optimize […] higher education process toward increased graduation rate" (p. 212). It used reflective statistics and student performance analytics to "nudge" learners toward better outcomes. It tracked semester performance, if the students would be eligible for a pass with 'good', and graduation class trajectories, providing tailored advice, actionable goals, and integration with academic advising. By showing current performance alongside areas for development, Auto-Ad encouraged self-directed learning and constructive engagement with support services, shifting attention from underperformance to achievable progress.

Despite the prominence of automated assessment in educational research, it appeared only marginally in the learner-support-focused corpus. This likely reflects that AI-based assessment is more often explored in course-specific or individual work contexts rather than within the broader learner support framework.

Intelligent tutoring systems (ITS) in learner support phases

There was also only one ITS study within the Learner Support phase. Lu (2019) focused on content-relevant automated feedback, examining the use of the automated writing evaluation system JUKU Pigai.org in English teaching in China through a mixed-methods design involving pre–post tests with 114 students and qualitative analysis of 198 students and 30 teachers. The system was valued for immediate feedback on grammar, organization, revision, and content, but students still preferred teacher input due to occasional inaccuracies and the need for a human touch.

Despite the extensive literature on ITS in ODDE, the lack of studies identified in this systematic review could be due to the high domain specificity of ITS. The transferability to larger domains is not easy (Karakostas & Demetriadis, 2014).

RQ 2: What practical experiences and constraints are documented in the literature?

Across the corpus, 55 studies reported positive experiences or implications, while 23 studies identified some constraints to be taken into consideration. These categories are not mutually exclusive, as some studies reported both positive experiences and constraints. Four studies did not specify any positive or negative experiences (Table 9).

Table 9

Practical experiences with AI-enabled support

Codes	Frequency			
	P&P	A&E	AS & P	ITS
Quick/Effective solution	3		10	2
Accessible and continuous support			8	
Tailored support	9	1	13	1
User friendly			5	

Codes	Frequency		
Less workload for support providers	1	6	1
Accurate information access	1	7	
Better learning quality	4	2	1
Early intervention	13	1	
Cost-effective		4	
Intrinsic motivation		1	

Tailored support was the most mentioned benefit (n = 24; e.g., Abdul et al., 2024; Becerra et al., 2024; Karakostas & Demetriadis, 2014; Öncü et al., 2025). It was followed by early intervention (n = 14) as well as a quick and effective solution (n = 14). With timely predictive analysis, institutions can increase retention by early interventions such as identifying students at risk with their risk levels (Villano et al., 2018); sending motivational nudges (Herodotou et al., 2020) or reminders as a warning for assignment submissions (Rodriguez et al., 2022).

Accessible and continuous support was also mentioned strongly across the corpus, which was mainly the result of facilitating chatbots. Overcoming the working hour barriers as well as faculty/staff's slow response times (Thongda & Songpan, 2023), learners could use chatbots for quick answers to frequently asked questions (e.g., Öncü et al., 2025; Prasertsri et al., 2024; Wangwiwattana & Jantarick, 2024) or to ask for help in an emergency (e.g., Balderas et al., 2023).

Timely intervention is a key factor of proactive support, and institutions seek to find a solution to help students on time and get in touch with them on the particular issue they are seeking an answer for. We know proactive student support is cost-effective for the institution as compared to reactive systems (Boyle et al., 2010; Budash et al., 2017). However, for institutions operating at scale, a human-powered mass-service structure also requires costly and complex structuring (e.g., Öncü et al., 2025). Therefore, the corpus shared the experience that a chatbot service that is available for 24/7 and answering questions accurately increased the satisfaction (Ndunagu et al., 2025; Pansombut & Kirimasthong, 2025; Karakostas & Demetriadis, 2014); created less workload for teachers (e.g. Herodotou et al., 2019; Honson et al., 2024; Lu, 2019) and for student support officers (e.g. Hardi et al., 2022; Öncü et al., 2025; Prasertsri et al., 2024).

Studies also reported the constraints as well as the inherent limitations of the current AI-enabled supports (Table 10).

Table 10

Constraints about AI-enabled support

Codes	P&P	A&E	AS & P	ITS
Data security			4	
Limited human interaction			4	1
Technical constraints	3		9	1
Need for more factor integration	4	1	2	1
Emotional distress	1			
Technology acceptance	1			

Current use of chatbots in the corpus was predominantly discussed in relation to technical constraints, including the continuous need for model maintenance and updates (e.g., Alves-Noreña et al., 2025; Balderas et al., 2023), reliance on accurate or exact language input (e.g., Lucien & Park,

2024; Lytridis & Tsinakos, 2025), inability to recognize nuanced inquiries (e.g., Pansombut & Kirimasthong, 2025; Wangwiwattana & Jantarick, 2024), and, in one case, inability to detect implicit, non-verbalized emotions (e.g., Alves-Noreña et al., 2025). Among the three studies utilizing LLMs, two (Öncü et al., 2025; Priccilia & Girsang, 2024) reported that LLM-based chatbots generated better answers overall; however, a generative chatbot was found to be non-contextual and unhelpful when domain-specific responses were required, which is a limitation attributed to the lack of integration of LLMs with institutional systems and data sources (Wangwiwattana & Jantarick, 2024).

Predictive models face constraints, mislabeling of at-risk students due to success depending on engagement in only certain activities or time periods (Honson et al., 2024); limited transferability of models as ongoing data renewal alters training across contexts (Gray & Perkins, 2019); and the risk of speculative conclusions from dashboards, even when data is validated with attention to extraction timestamps, as visualizations provide only snapshots (Chong et al., 2020).

The need for more data input was another item. While having a predictive model on using data on how frequently a student accessed a learning management system, the model would perform better if study duration was also captured (e.g., Honson et al., 2024).

Data security and privacy was also, though not frequently, a reported constraint. The importance of proper management of emotional data privacy and confidentiality is essential (Alves-Noreña et al., 2025) as especially chatbots might handle sensitive information (Ndunagu et al., 2025; Ula et al, 2023). Therefore, transparency in data processing, sharing, and storage are recorded as the essential elements (Ndunagu et al., 2025).

The absence or reduction of human interaction was identified as a further drawback (e.g., Hanshaw et al., 2024; Ula et al., 2023), with recommendations that AI interventions serve as a complement rather than a replacement (Hanshaw et al., 2024). Avoiding overreliance on AI and preserving human connection were emphasized as essential (Lu, 2019; Ndunagu et al., 2025; Ula et al., 2023). Similarly, Öncü et al. (2024) found that learners experienced a diminished sense of human engagement.

RQ 3: To what extent do current AI-driven learner support services address the diverse needs of learners?

Across the corpus, AI applications largely approached “the learner” as a uniform category. Very few studies engaged with differentiated needs such as those of neurodivergent learners, minority groups, or socio-economically marginalized students. Only two studies explicitly referenced subgroups (Candrlić et al., 2025; Nurshhatayeva et al., 2021), and only one proposed a support model centred on a disadvantaged student group (Candrlić et al., 2025).

Candrlić et al. (2025) developed a process model for support services, grounded on the framework of the United Nations Convention on the Rights of Persons with Disabilities (UN CRPD, 2006, as cited in Candrlić et al., 2025). The model maps the main activities of the Academic Accommodations Counselling unit, such as counselling, training, and reporting, through data flow diagrams. It was developed through interviews with experienced AAC staff who informed the design based on longstanding practice. The authors propose integrating AI throughout the process, including conversational tools to explain rights and services, machine learning to recommend accommodations, accessible content tools such as text-to-speech and captioning, automated scheduling for meetings and assistance, and sentiment analysis to capture user feedback.

Nurshatayeva et al. (2021) assessed a chatbot intervention for all new students at East Carolina University using institutional data. Although average use did not differ by first-generation status, the most intensive engagement came from first-generation students, who also showed lower baseline completion of pre-enrollment tasks. For this group, the intervention increased loan uptake by about eight percentage points and raised both enrollment and course registration by roughly three points compared to controls. The overall positive effects were therefore concentrated among first-generation students, consistent with evidence that summer melt disproportionately affects students with fewer resources.

Beyond these cases, the corpus did not address neurodivergent learners or minority ethnic, linguistic, or low-income student populations. This absence highlights concerns about inclusivity in AIEd, including the risk of systems optimized around majority experiences and therefore disadvantaging others (Dixon-Román et al., 2020; Selwyn, 2024). Designs premised on an imagined "typical" learner may overlook important sociocultural variation, while meaningful inclusion requires more granular data on disability status, language backgrounds, and other relevant characteristics.

However, this result wrestles with a further issue of "marginal privacy" (Skinner-Thompson, 2020). Prinsloo et al. (2022), in reference to Skinner-Thompson (2020), discuss in detail how neutral privacy protections often fail to safeguard individuals in intersectional and marginalized demographic groups. In educational contexts, highly granular data aimed at personalized support may inadvertently enable intensified monitoring or reproduce structural inequities. However, ignoring what are often called 'attributes' (demographic data) in favour of 'behaviours' (attendance, paying attention, etc.) in order to nudge learners towards behavioural change, also reproduces structural inequities, by placing sole responsibility for success on individual students (Whitman, 2020; Decuypere & Hartong, 2023).

Therefore, balancing the envisioned potential of AI-enabled support with safeguards against the entrenched biases of data-driven monitoring is essential to avoid deepening existing inequities. Protecting marginalized students from harm (via marginal privacy or stronger safeguards) requires, for instance, ensuring such attributes are not easily identifiable or inferable. Methods for designing differently (Toupin, 2024), including co-designing with heterogeneous groups have been developed (Frauenberger et al., 2019), but were not used in the papers reviewed here.

Conclusion and Implications

This study examined the facilitation of AI-enabled learner support in ODDE, applying two complementary conceptual frameworks to structure the analysis. The AI typology (Zawacki-Richter et al., 2019) provided a functional context for classifying applications, focusing on what the tools do rather than their shifting brand names or technical architectures. The ISSPM (Floyd & Casey-Powell, 2004) situated these interventions along the learner's institutional journey, namely, from intake and intervention, through ongoing support, to the measurement of outcomes such as retention and programme evaluation.

In this study, we excluded individual practice-based investigations that indirectly support students by employing AI technologies in classroom contexts to enhance learning experiences. We recognize, however, that a growing body of research highlights how students are independently using AI agents to check their writing, revise language, or even generate texts. The initial fast, albeit not always rigorous, publications (Weidlich et al., 2025), emphasizing how AI could rapidly assist teachers and learners, have been challenged by more critical research over recent decades (e.g., Selwyn et al., 2025; Williamson & Eynon, 2020). Unlike earlier technological waves that typically

required structured, institutional adoption, the enthusiasm surrounding AI today is fueled by its direct availability to individuals outside formal educational systems. This shift has drawn more attention to scholarly discussions beyond the more narrow focus on interactive tutoring systems' direct effect on individual students, and toward the broader debates encompassing issues of post-truth, data colonization, and the ethical as well as societal implications of AI (Bozkurt, 2023; Bozkurt et al., 2024; Williamson et al., 2023).

In this context, it is unsurprising that relatively few publications appeared in the learner support intervention. In this review, we did not see the same rapid response trend - especially to generative AI advancements - in learner support interventions, except for the increase in the chatbot interventions. The studies also tended to adopt a cautious rather than overtly promotional stance toward AI adoption. The overly enthusiastic public-domain discourses surrounding AI were notably absent from this body of research.

Despite their potential, these interventions also raise important questions about data privacy and long-term ethical stewardship. The contractual relationship between learners and institutions is rarely transparent about how support-related data will be used beyond the period of active study. Consent, in practice, often extends over years as historical data fuels predictive models. As Prinsloo et al. (2022) and Taylor et al. (2016) caution, clustering learners by shared attributes—even for seemingly helpful purposes such as social-based course scheduling—can produce aggregate-level risks, reinforcing inequities or making sensitive traits indirectly identifiable. Institutions must therefore treat privacy not as an individual checkbox but as a systemic ethical responsibility.

Equity and inclusiveness also remain underdeveloped. Most interventions target a generalized, homogeneous student body. Specific provisions for marginalized groups, neurodivergent learners, or linguistic minorities are almost absent. Mental well-being and mentoring, peer-support and community building received minimal attention. The Learner Transition phase is untouched by AI-enabled support in the reviewed corpus, and the recent hype around large language models has not yet translated into deployment for learner support. We see this absence, in the short term, as a safeguard against premature or poorly integrated adoption. In the long term, however, it should not result in certain groups being excluded from the development of support interventions.

These gaps matter because the benefits of technological innovation often carry rebound effects: Efficiency can lead to over-automation, personalization can enable over-surveillance, and scaling up can amplify systemic biases. To realize AI's full potential for learner support in ODDE, future work should:

- extend interventions across the full ISSPM spectrum, especially in transition and mentoring stages;
- embed equity and inclusivity as core design principles rather than afterthoughts;
- strengthen consent practices and transparency over long-term data use; and
- develop hybrid models where AI augments, rather than displaces, human support relationships.

This review provides a first structured synthesis of AI-enabled learner support in higher education and identifies key limitations in current research and practice. AI-driven systems predominantly conceptualize learners as homogeneous data points, with limited attention to diversity and inclusion, while institutional applications remain largely confined to prediction-based approaches. These patterns reveal a disconnect between institutional AI implementations and the complex needs of

learners. The findings highlight the need for more learner-centered, inclusive, and ethically grounded approaches, and offer a foundation for future research and practice in this emerging field.

Our findings are consistent with broader critiques in the AI and disability literature. As with other ICT opportunities, AI is frequently presented as a promising means of enhancing accessibility, autonomy, and educational participation for students with disabilities (Fichten, 2000; Fichten et al., 2014; Martiniello et al., 2020). However, evidence suggests that these benefits remain unevenly distributed (Lillywhite & Wolbring, 2020). AI-powered tools can facilitate learning through personalized support, assistive technologies, conversational agents, and adaptive services that respond to individual needs. However, as our synthesis demonstrates as well, AI applications are based on a uniform understanding of students and employ no diverse student experiences. Concurringly with a number of studies (e.g., Trewin et al., 2019), AI applications in education frequently rely on datasets and assumptions derived from normative learner populations about learner behaviour and performance, potentially disadvantaging students whose learning trajectories, interaction patterns, or support requirements fall outside dominant expectations. Consequently, those who stand to benefit most from AI-supported learning may also be the most vulnerable to exclusion, misclassification, or ineffective support. Their call for human-centred and inclusive AI development directly reinforces our conclusion that learner support systems should more actively account for learner diversity.

The broader pattern we identified in our review, whereby learners are often positioned as objects of analysis rather than as participants in the design and evaluation of AI-supported services, concurs with what Lillywhite and Wolbring (2020) highlighted in their study. The disabled people are largely absent from AI-related academic, media, and public discourses as active stakeholders, knowledge producers, and contributors to governance discussions. Instead, they are predominantly portrayed as users or recipients of AI-enabled technologies despite a long-standing co-design call (Fichter et al., 2000; Fichten et al., 2019; Martiniello et al., 2020; Trewin et al., 2019).

Accordingly, the findings of this review have several practical implications for educators and institutional decision-makers. First, institutions should critically reflect on the assumptions embedded in AI-driven learner support systems, particularly the tendency to conceptualize learners as homogeneous groups. Second, AI-based support tools should be complemented by human-centered support structures to ensure that diverse learner needs (especially those of underrepresented or disadvantaged groups) are adequately addressed. Third, transparency in data use and algorithmic decision-making processes is essential to maintain trust and align with ethical standards in learner support. Furthermore, current implementations, which predominantly focus on prediction-based applications such as early warning systems, should be expanded toward more holistic and pedagogically grounded support approaches. Finally, establishing co-design culture with all stakeholders is crucial. Thus, academic and non-academic support points will be able to critically evaluate and effectively integrate AI-supported learner services into their practice.

Across the research reviewed in this paper, AI was summoned for help as a powerful tool to enhance responsiveness, scalability, and personalization in ODDE learner support. However, if these studies do not pay deliberate attention to ethics, equity, and the human dimension, these systems risk reinforcing the very challenges they aim to solve.

Declarations

Conflicts of Interest Statement

The authors declare no conflicts of interest related to the research, authorship, or publication of this article.

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Appendices and Supplemental Materials

For the following list of appendices, please see: https://osf.io/gyc5z

Appendix A: Country of the first author
Appendix B: Subcategories of department affiliations
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Appendix E: Coding list