Generative AI for Self-Instructional Materials in ODL: A Scoping Review of Higher Education Studies

Noridah Abu Bakar*

*Faculty of Sports Science and Recreation, Universiti Teknologi MARA, Malaysia

*Corresponding Author

DOI: https://doi.org/10.47772/IJRISS.2026.101000736

Received: 25 October 2026; Accepted: 30 October 2026; Published: 17 November 2026

ABSTRACT

Generative artificial intelligence (GenAI) tools such as ChatGPT are transforming how lecturers develop teaching materials. However, limited research has explored their application in developing self-instructional materials (SIMs), which play a crucial role in supporting teaching and learning in Open and Distance Learning (ODL) environments. This scoping review used AI-assisted semantic platforms, specifically Scopus AI and Consensus, to identify literature published from January 2020 to August 2026 and mapped how lecturers use AI to develop instructional materials, which theories explain adoption, which challenges are reported, and where gaps remain. In total, 17 sources were analysed. These included eight empirical studies, three systematic or scoping reviews, one narrative review, one institutional policy analysis and four conceptual papers, all published from 2023 to 2026. Lecturers used GenAI to plan lessons, draft content, generate quizzes and assessments, and produce personalised multi-style modules. Trust, departmental social reinforcement, and the fulfilment of psychological needs were the strongest predictors of adoption; evidence on usefulness versus ease of use was mixed, and individual self-efficacy had little direct effect. Lecturers remained cautious about inaccurate or fabricated content, students' cognitive outsourcing, limited training, and unclear institutional policy. The evidence is mostly cross-sectional, and no included study was set in Southeast Asia or in a dedicated ODL institution, so implications for ODL are inferred rather than observed. The review proposes a human-in-the-loop framework for AI-assisted SIM development and an agenda for ODL-based research, ethical governance, and professional development in critical AI literacy.

Keywords: Generative Artificial Intelligence, Self-Instructional Materials, Open and Distance Learning, Faculty Readiness, Scoping Review

INTRODUCTION

Open and Distance Learning (ODL) depends on self-instructional materials (SIMs): structured modules, guided readings, activities and self-assessments designed to teach in the absence of a lecturer. Because ODL learner's study location is often temporally distant from their instructors, the quality of these materials largely determines how well they bridge the gap in dialogue and structure (Moore, 1993). Producing SIMs is labour-intensive: lecturers must translate learning outcomes into sequenced content, embed formative questions and feedback, and revise materials as disciplines evolve, often alongside heavy teaching and research loads.

Generative artificial intelligence (GenAI) has penetrated higher education at an unprecedented rate since ChatGPT's public release in late 2022, and research on it has grown rapidly (Qian, 2025). Large language models can draft explanations, summarise readings, propose lesson plans, and generate quizzes and feedback within seconds, creating opportunities as well as new risks (Kasneci et al., 2023; Crompton & Burke, 2023). International guidance calls for a human-centred approach in which educators retain responsibility for the accuracy and ethical use of AI-generated content (Miao & Holmes, 2023). For ODL, where SIMs are the main teaching voice, these questions are particularly consequential.

Previous studies evaluating the use of AI in higher education have covered a broad range of topics. Zawacki-Richter et al. (2019) found little critical reflection on the pedagogical and ethical implications of AI applications, and a later meta-systematic review called for greater ethics, collaboration and rigour (Bond et al., 2024). Recent syntheses of GenAI have examined curriculum, instruction and assessment generally (Liang et al., 2025; Qian, 2025), faculty perceptions (Buele & Llerena-Aguirre, 2025) or a single discipline (Basil et al., 2026). However, to the best of the author's knowledge, no previous review has specifically examined how lecturers use AI to design and develop self-instructional materials for Open and Distance Learning (ODL). The present scoping review seeks to address this gap by systematically mapping the existing literature on AI-assisted instructional material development in ODL contexts.

Several theoretical lenses explain why lecturers adopt or resist these tools. The Technology Acceptance Model (TAM) emphasises perceived usefulness and ease of use (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT) adds social influence and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2016). Social Cognitive Theory (SCT) foregrounds self-efficacy (Bandura, 1999), Self-Determination Theory (SDT) explains motivation through autonomy, competence and relatedness (Ryan & Deci, 2000), and Activity Theory treats GenAI as a mediating artefact that reshapes academic work (Engeström, 1987). Despite efficiency gains, lecturers remain ambivalent because of concerns about reliability, academic integrity, pedagogical alignment and incomplete institutional support (Buele & Llerena-Aguirre, 2025; Kohnke et al., 2023).

Given the limited research on GenAI in dedicated Open and Distance Learning (ODL) institutions, this review maps existing evidence on how lecturers in higher education use AI to develop instructional materials and considers its implications for the design of self-instructional materials (SIMs) in ODL contexts. It examines which uses are reported, which theories explain adoption, which challenges constrain integration, and where evidence remains thin. Its contribution is fourfold: it consolidates dispersed evidence on lecturer practice, compares competing adoption theories, organises research gaps into a structured agenda, and proposes a human-in-the-loop framework for AI-assisted SIM development.

METHODOLOGY

Review Design

A scoping design was chosen to map the extent and thematic nature of this emerging, heterogeneous literature rather than estimate pooled effect sizes. The methodology adapted the exploratory framework of Arksey and O'Malley (2005) to accommodate AI-assisted literature retrieval rather than a standard PRISMA protocol. Primary evidence was identified using semantic, AI-powered discovery platforms, specifically Scopus AI and Consensus. Searches were executed using iterative natural language queries to retrieve, contextualise, and synthesise the relevant evidence base.

Stage 1: Identifying the Research Questions

- **RQ1:** How do lecturers use AI technologies to design and adapt instructional materials, including self-instructional materials, across disciplines in higher education and ODL?
- **RQ2:** Which theoretical models explain faculty acceptance, trust, social influence and readiness regarding AI adoption?
- **RQ3:** What pedagogical, ethical, technical and institutional challenges hinder the integration of AI in instructional material development?
- **RQ4:** What theoretical, methodological, population, contextual and practical gaps exist in the literature?

Stage 2: Identifying Relevant Studies

Two AI-assisted discovery tools were searched in August 2026: Scopus AI, the generative AI search tool built on the Scopus database, and Consensus, an AI-assisted academic search engine that retrieves peer-reviewed papers from the Semantic Scholar corpus. Every tool was prompted in natural language, then the query was continually improved, and all records that were returned were filtered using the same standards. The first prompt for each is shown in Table 1. The reference lists of included studies were also manually screened to identify additional relevant literature.

Table 1. Search sources and initial prompt

Source	Search query/prompt
Scopus AI	Find peer-reviewed studies on lecturers' use of AI to develop self-instructional/instructional materials for Open and Distance Learning (ODL) in higher education. Focus on AI/Generative AI/ChatGPT, lecturers' practices, challenges, opportunities, competencies, support, and pedagogical or ethical issues. Identify relevant studies, key themes, research gaps, methods, participants, countries, and AI technologies. Do not invent references or findings.
Consensus	How do lecturers use generative AI to design instructional materials in higher education and distance learning, and what factors and barriers affect their adoption?

Stage 3: Study Selection

Records were exported to Mendeley and a CSV file, duplicates were eliminated, and two steps of screening—title and abstract first, then full text were conducted using the criteria listed in Table 2. The author completed the screening and charting. Out of the 23 records initially retrieved (15 from Scopus AI and 8 from Consensus), 4 duplicate records were removed. Following full-text screening, 2 articles were excluded due to institutional inaccessibility, resulting in a final corpus of 17 included sources. To limit error, every included full text was re-read, and each finding is reported accordingly. Results were checked against the original source rather than tool-generated summaries; AI-generated summaries produced by the search tools were used only to orient screening and were not treated as evidence. Since the evidence base is young, conceptual papers offering design principles or adoption strategies were retained alongside empirical studies and reviews, consistent with scoping methodology (Peters et al., 2020). Two studies with student participants were retained because they report learners' responses to GenAI-supported learning, including concerns about accuracy and over-reliance, which inform how SIMs should be designed (Table 2).

Table 2. Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Population	University lecturers, faculty or institutions in higher education or ODL; student data where it informs instructional design	School-level or corporate training only
Concept	Use, perception, adoption or governance of AI (especially GenAI) for designing, generating or adapting instructional, self-instructional or assessment materials	AI used only for administration or admissions, with no link to teaching materials
Source type	Empirical studies, systematic or scoping reviews, policy analyses, and conceptual papers proposing design principles or strategies	Editorials, news items, and AI-generated reports without an identifiable author
Period and language	January 2020 – August 2026; English	Outside this period; non-English

Stages 4 and 5: Charting, Compiling and Reporting

A charting form captured author, year, country, design, sample, AI tool, type of instructional material, theoretical framework, key findings and challenges. Data were summarised descriptively and analysed thematically (Braun & Clarke, 2006) against the four RQs. Consistent with scoping methodology, study quality was not formally appraised (Peters et al., 2020).

RESULTS

Characteristics of the Included Sources

Seventeen sources met the inclusion criteria (Table 3). Although the search began in 2020, every included source was published after the release of ChatGPT: three in 2023, six in 2024, five in 2025 and three in 2026. The corpus comprised eight empirical studies (five quantitative surveys, one of them a 30-participant pilot; one mixed-methods study; one qualitative case study; and one design-based tool evaluation with a six-month follow-up questionnaire), three systematic or scoping reviews, one narrative review, one analysis of institutional policies, and four conceptual papers. Lecturers were the participants in six empirical studies and students in two. No included source was conducted in Southeast Asia or Africa, and none was set within a dedicated ODL institution; this describes the corpus retrieved by the present search rather than the wider literature.

Table 3. Charting summary of the 17 included sources

#	Source	Context	Design (sample)	Focus and key contribution
1	Atchley et al. (2024)	USA	Conceptual	Cognitive-science view of human–AI collaboration; risks of fabricated citations and cognitive outsourcing
2	Basil et al. (2026)	Multi-country	Scoping review	GenAI in health profession education, e.g., generation of clinical vignettes and illness scripts
3	Buele & Llerena-Aguirre (2025)	Multi-country	Narrative review (9 empirical studies)	Faculty perceptions and barriers (training, support, unclear policy); transformation of academic work
4	Chan & Hu (2023)	Hong Kong	Survey (399 students)	Student perceptions of GenAI benefits and challenges
5	Chang et al. (2023)	Not country-specific	Conceptual / design principles	Chatbot design for self-regulated learning: goal setting, feedback, personalisation
6	Cordero et al. (2025)	Ecuador	Mixed methods (184 teachers and staff)	Training needs; GenAI for writing and educational resources; best practices
7	Ismayil et al. (2026)	Azerbaijan	Pilot survey (30 faculty)	Faculty AI literacy, perceived usefulness and risk, willingness to use and integrity concerns
8	Kohnke et al. (2023)	Hong Kong	Qualitative case study (12 English language instructors)	Preparedness and competencies needed to teach with GenAI
9	Kurtz et al. (2024)	Middle East	Conceptual / position paper	Integration strategies; four-level faculty adoption scale
10	Liang et al. (2025)	Multi-country	Systematic review (33 studies)	Early impact of AI on curriculum, instruction and assessment
11	Luo & Day (2026)	China	Survey (651 lecturers; SEM)	UTAUT integrated with SDT; need fulfilment strongest predictor of intention
12	Mah & Groß (2024)	Germany	Survey (122 faculty; latent class analysis)	Faculty AI use, self-efficacy, profiles and professional development needs

13	Nikolopoulou (2024)	Greece	Conceptual	Ways to harness ChatGPT in pedagogical practice
14	Pesovski et al. (2024)	North Macedonia	Design-based tool evaluation (20 students; six-month follow-up)	LMS–OpenAI tool generating multi-style materials and quizzes from lecturer outcomes
15	Qian (2025)	Multi-country	Systematic review (37 studies)	Pedagogical applications of GenAI in higher education
16	Shata & Hartley (2025)	USA	Survey (294 faculty; TAM and SCT)	Trust, social reinforcement and usefulness drive adoption; self-efficacy has minimal effect
17	Wang et al. (2024)	USA	Policy document analysis (104 universities)	Institutional GenAI policies, resources and guidelines

RQ1: How Lecturers Use AI to Develop Instructional Materials

Because no included study examined SIMs in a dedicated ODL institution, this section maps lecturers' use of GenAI for instructional materials in higher education and highlights the uses most transferable to SIM development. Lecturers used GenAI to produce a range of material components, including quizzes, summaries, lecture slides, assignments and reading-comprehension items (Basil et al., 2026; Nikolopoulou, 2024), and the generation of new material and the automation of assessment were among the main applications identified across curriculum, instruction and assessment (Liang et al., 2025). In an Ecuadorian university, 62% of surveyed teachers reported that ChatGPT helped them generate educational resources and 70% reported that it improved their writing, although only 1% reported advanced knowledge of the tool (Cordero et al., 2025).

Disciplinary adaptation. Uses varied by field. In language education, GenAI supported writing feedback, grammar correction and conversational practice (Qian, 2025), and university language instructors reported needing specific technological and pedagogical competencies to teach with it (Kohnke et al., 2023). In software engineering, GenAI generated complete lessons and quizzes from lecturer-defined learning outcomes (Pesovski et al., 2024). In health professions education, GenAI was used to generate clinical vignettes and illness scripts, but in one included study only about three in five GPT-4-generated cases were medically accurate, underlining the need for expert review before use (Basil et al., 2026).

Personalisation and self-regulation. The clearest demonstration of AI-supported SIM design comes from software engineering, where a tool embedded in an existing learning management system used the OpenAI API to turn lecturer-entered learning outcomes into materials in three styles (a conventional professor voice and two pop-culture personas) with automatically generated quizzes. Study time increased, especially among students who had not mastered the topic, and students predominantly used the traditional style; a second questionnaire six months later examined longer-term perceptions, although learning outcomes were not measured (Pesovski et al., 2024). The lecturer approved every generated lesson before release, an early instance of human-in-the-loop design. Complementary design principles (goal setting, feedback and personalisation) show how AI chatbots can scaffold the self-regulated learning that SIMs require (Chang et al., 2023).

RQ2: Theoretical Explanations of Faculty Adoption

The two adoption surveys converge on the importance of trust, social influence and motivation but differ on usefulness and ease of use. In a combined TAM–SCT model tested with 294 United States faculty, perceived usefulness influenced attitudes and intention considerably more than perceived ease of use, trust was the strongest predictor, and departmental social reinforcement shaped adoption mainly through trust, whereas individual self-efficacy had minimal direct impact (Shata & Hartley, 2025). Integrating UTAUT with SDT in a survey of 651 Chinese lecturers, Luo and Day (2026) found that fulfilment of the needs for autonomy, competence and relatedness was the strongest predictor of behavioural intention; performance expectancy and effort expectancy were both significant, with effort expectancy slightly stronger, and facilitating conditions predicted both intention and actual use. Activity Theory, which frames GenAI as a

mediating artefact that reshapes academic work (Engeström, 1987), has been proposed as a lens but was not applied in any included study.

Faculty was not a homogeneous group. Latent class analysis of 122 German faculty members identified optimistic (33.5%), critical (27.3%), critically reflected (33.9%), and neutral (5.3%) profiles, highlighting the need for tailored professional development strategies to support digital transformation (Mah & Groß, 2024). AI literacy also mattered: in an Azerbaijani pilot survey of 30 faculty, AI literacy correlated strongly with perceived usefulness ($r = .76$), and higher-literacy adopters redesigned their assessments around process-oriented approaches (Ismayil et al., 2026). Across studies, lecturers asked for tailored training and institutional support (Cordero et al., 2025; Kohnke et al., 2023). Kurtz et al. (2024) accordingly proposed a four-level adoption scale with actions to move faculty between levels. Together, the evidence portrays adoption as a motivated, social and staged process rather than an individual technical decision.

RQ3: Benefits, Challenges and Institutional Gaps

Table 4 contrasts the benefits and challenges reported across the corpus.

Table 4. Reported benefits and challenges of AI-assisted SIM development

Domain	Reported benefits	Reported challenges
Pedagogical	Faster lesson planning and assessment item generation; multi-style, personalised modules (Cordero et al., 2025; Pesovski et al., 2024)	Cognitive outsourcing of writing, analysis and critical thinking (Atchley et al., 2024)
Content quality	Quick drafts, quizzes and case vignettes for lecturer refinement (Basil et al., 2026; Liang et al., 2025)	Inaccurate content and fabricated citations requiring expert review (Atchley et al., 2024; Basil et al., 2026)
Equity and access	Low marginal cost of producing material variants (Pesovski et al., 2024)	Digital divide and unequal access to tools (Kurtz et al., 2024)
Institutional	Faster production of educational resources (Cordero et al., 2025)	Limited training and support; unclear policies; detection-centred guidance (Buele & Llerena-Aguirre, 2025; Wang et al., 2024)

Quality and cognitive risk. Lecturers and authors remained cautious about inaccurate and fabricated content. Fabricated citations are difficult to detect because they mimic real authors and journals (Atchley et al., 2024), and generated clinical cases needed expert correction before use (Basil et al., 2026). Conceptual work stressed that GenAI output requires human evaluation and raised ethical concerns about data privacy, transparency and cultural sensitivity (Nikolopoulou, 2024). Authors also warned that student over-reliance could outsource writing, analysis and critical thinking (Atchley et al., 2024). Students voiced similar concerns about accuracy and over-reliance while valuing personalised support (Chan & Hu, 2023).

Institutional Support and the Reliability of AI Detection Tools. Integration was frequently hampered by a lack of training, a lack of institutional support, and unclear policies (Buele & Llerena-Aguirre, 2025; Cordero et al., 2025; Kohnke et al., 2023). An analysis of 104 leading U.S. universities found that none had banned GenAI; 54.8% delegated policy to individual instructors, and among these universities prohibition by default (47.4%) and neutrality (50.9%) were the most common positions (Wang et al., 2024). Although 56.7% of these universities discussed detection tools such as Turnitin and GPTZero, none regarded them as completely reliable or endorsed their use to determine plagiarism (Wang et al., 2024). The limitations of detection-led policy are highlighted by the fact that just 19% of Ecuadorian educators felt comfortable recognising AI-generated content (Cordero et al., 2025).

RQ4: Gaps in the Literature

Gaps were identified across five domains. Table 5 pairs each gap with the research direction it implies.

Table 5. Research gaps and agenda for future research

Domain	Gap identified in the corpus	Recommended research direction
Theoretical	Reliance on TAM/UTAUT; only one study integrated SDT (Luo & Day, 2026); Activity Theory proposed but not applied in any included study; mixed evidence on usefulness versus ease of use (Luo & Day, 2026; Shata & Hartley, 2025)	Integrative models combining acceptance, motivational and activity-system constructs, tested in ODL
Methodological	Mostly cross-sectional surveys, including a 30-participant pilot (Ismayil et al., 2026); the only follow-up had 20 participants and measured perceptions rather than learning (Pesovski et al., 2024)	Longitudinal and quasi-experimental evaluation of AI-developed SIMs on learning, integrity and skill retention
Population	Lecturer samples were mixed-discipline or drawn from language, social sciences and humanities; no instructional designers or ODL course writers	Studies of instructional designers and ODL course writers; discipline-specific and cross-stakeholder comparisons (lecturers, designers, administrators)
Contextual	No included Southeast Asian, African or dedicated ODL-institution study; no included evaluation of AI-generated materials in languages other than English	Malaysian and ASEAN ODL studies; evaluation of AI-generated SIMs in Malay and other local languages
Practical	Few evaluations beyond ChatGPT; no validated AI-literacy or governance framework for SIM design	Comparative evaluation of adaptive systems and chatbots; validation of AI-literacy and review frameworks

DISCUSSION

An Operational Paradox

The synthesis reveals an operational paradox. Lecturers acknowledge that GenAI can speed up the production of instructional materials and personalise them (Cordero et al., 2025; Pesovski et al., 2024), yet limited training, limited institutional support and unclear policies impede integration (Buele & Llerena-Aguirre, 2025; Kohnke et al., 2023). Institutional responses are misaligned with this potential: guidance that emphasises detection persists even though leading universities themselves do not regard detectors as reliable (Wang et al., 2024), while sustained professional development remains scarce (Buele & Llerena-Aguirre, 2025). Adoption is also uneven: faculty fall into optimistic, critical, critically reflective, and neutral profiles with different support needs (Mah & Groß, 2024), and AI literacy is closely tied to how useful lecturers find the tools (Ismayil et al., 2026).

Adoption as a Motivated and Social Process

Read together, the theories indicate that acceptance is a social and motivational process. That trust and departmental reinforcement matter more than individual self-efficacy (Shata & Hartley, 2025), and that psychological need fulfilment is the strongest predictor of intention (Luo & Day, 2026), has a direct implication: one-off skills workshops are unlikely to change practice. Distinct faculty profiles (Mah & Groß, 2024) further suggest that support should be differentiated, offering critical faculty evidence of accuracy and pedagogical value and offering optimistic faculty guidance on responsible limits.

Towards a Human-in-the-Loop Framework

Drawing these findings together, this review conceptualises an original human-in-the-loop framework for AI-assisted SIM development (Figure 1). The suggested framework reorganises material production into a faculty-guided, five-step iterative cycle. It is based on the traditional principles of instructional systems design, specifically adapting the five phases of the ADDIE model (Analysis, Design, Development, Implementation, and Evaluation; Branch, 2009) to an AI-mediated environment. In this workflow, baseline lecturer readiness drives the development cycle:

1 Plan : Outline specific learning objectives.
2 Generate : Produces quick AI-driven drafts of learning material variations, assessment questions, and instructional modules.
3 Verify : Re-engineers the traditional Development phase, wherein AI-generated content is strictly evaluated by subject matter experts to identify and rectify hallucinations, algorithmic bias, and copyright infringements.
4 Align : Prepares materials for Implementation through pedagogical calibration and personalisation, echoing the human-moderated approval protocol established by Pesovski et al. (2024); and
5 Evaluate : Sustains the Evaluation phase by assessing empirical learner engagement and outcome attainment.

Throughout the process, institutional enablers act as essential moderating conditions at every tier. Rather than functioning as a rigid, automated pipeline, this framework positions GenAI purely as an assistive mediating artefact (Engeström, 1987), ensuring that pedagogical agency remains firmly with the educator. The model offers a conceptual synthesis for future empirical testing in dedicated ODL settings.

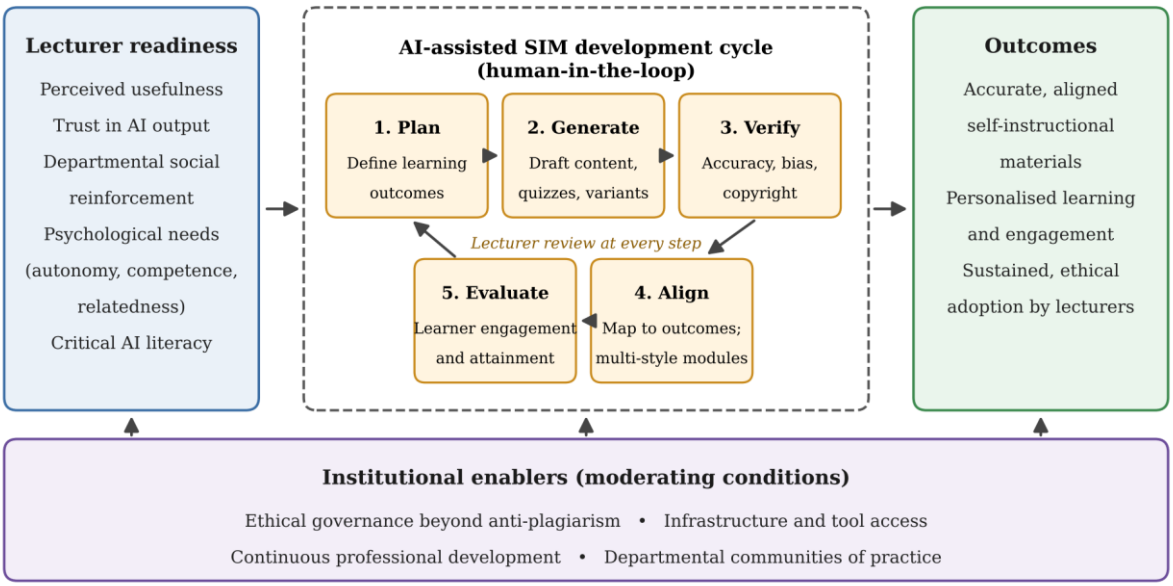


Figure 1. Proposed human-in-the-loop framework for AI-assisted SIM development in ODL
(Source: Author's Illustration)

Implications for Practice and Policy

For lecturers. Lecturers need prompt literacy and critical evaluation competencies (Atchley et al., 2024; Ismayil et al., 2026), acting as validators who review AI-generated case studies, quizzes and lesson outlines for accuracy, bias and hallucination before they reach independent learners (Nikolopoulou, 2024; Pesovski et al., 2024).

For ODL institutions. Leadership should replace purely defensive guidelines with infrastructure, clear pedagogical frameworks and ongoing, context-sensitive professional development delivered through communities of practice rather than one-off workshops (Luo & Day, 2026; Shata & Hartley, 2025), differentiated by faculty profile (Mah & Groß, 2024).

For assessment design. Rather than relying on detectors, institutions should adopt process-oriented assessment: scaffolded tasks with outlines, drafts, peer review and reflection; assignments tied to local or course-specific materials; and multimodal demonstrations of reasoning such as oral explanations and presentations (Cordero et al., 2025; Wang et al., 2024). For Malaysian ODL providers, these recommendations can be aligned with national higher education guidance on AI use.

Limitations

The review relied on two AI-assisted discovery tools (Scopus AI and Consensus) and English-language literature only, so relevant studies in other databases (for example, Web of Science or ERIC) or languages may have been missed; the absence of Southeast Asian and ODL-institution studies should therefore be read as a feature of the retrieved corpus. Consensus relies on a semantic ranking algorithm whose retrieval cannot be fully reproduced. One reviewer performed the screening and charting, which raises the possibility of selection and extraction errors. Four included sources are conceptual, so parts of the synthesis rest on argument rather than data, and study quality was not appraised. Because the evidence concerns higher education generally rather than ODL, implications for SIMs are inferred rather than observed, and the rapid evolution of GenAI may outpace the literature. Finally, the proposed framework requires empirical validation.

CONCLUSION

This scoping review mapped 17 sources on how lecturers use AI to develop instructional materials in higher education and interpreted them for self-instructional materials in ODL. GenAI already supports lesson planning, content generation, assessment design and personalisation. Its adoption depends strongly on trust, departmental reinforcement and psychological need fulfilment, whereas evidence on usefulness versus ease of use is mixed and individual self-efficacy has little direct effect. Lecturers remain cautious because of inaccurate and fabricated content, cognitive outsourcing, limited training and unclear or detection-centred policies. The evidence base is young and mostly cross-sectional, and no included study was conducted in Southeast Asia or in a dedicated ODL institution. Sustainable integration therefore requires institutional leadership that balances governance with pedagogical support, differentiated professional development in critical AI literacy, process-oriented assessment and human oversight at every stage of material development. The proposed framework and research agenda offer a starting point for Malaysian and international ODL institutions seeking to harness GenAI ethically, equitably and effectively.

Declarations

Ethical considerations. This study is a review of published literature and did not involve human participants or animals; ethical approval was therefore not required.

Conflict of interest. The author declares no conflict of interest.

Data availability. All data analysed are drawn from the published sources listed in the references.

Funding. This research received no specific grant from any funding agency.

Use of generative AI. Scopus AI and Consensus were used to support literature retrieval. Google Gemini Notebook was used to organise and summarise the retrieved sources, and an AI assistant was used for language editing and formatting. All sources were read and all content was verified by the author, who takes full responsibility for the manuscript.

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