IJELHE
e-ISSN: 3030-6663

Available online at
https://journalined.uitm.edu.my/

International Journal on e-Learning and Higher Education 21 (2) 2026, 81-93

International Journal on e-Learning and Higher Education

Transforming Static Self-instructional Materials (SIMs) into AI-enabled Learning Environments to Enhance Learner Achievement, Engagement, and Reduce Dropout Risk in Open and Distance Learning (ODL)

Noraini Seman, Prasanna Ramakrisnan, Norjansalika Janom*

Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM), Shah Alam, Selangor. MALAYSIA

ARTICLE INFO

Article history:
Received 28 September 2025
Revised 13 March 2026
Accepted 20 June 2026
Online first
Published 30 June 2026

Keywords:
AI-enabled
Dropout
Malaysian Qualifications Framework (MQF)
Open and Distance Learning (ODL)
Self-Instructional Materials (SIMs)
Transforming

DOI:
10.24191/ijelhe.v21n2.2129

ABSTRACT

Open and Distance Learning (ODL) has become an important approach to widening access to higher education while supporting Malaysia's aspirations for flexible and lifelong learning under the Malaysian Qualifications Framework 2.0 (MQF 2.0). Despite its widespread adoption, conventional Self-Instructional Materials (SIMs) remain largely static, providing limited support for personalised learning, learner analytics, and timely instructional intervention. This study presents the design, development, and evaluation of an AI-enabled SIM prototype that integrates adaptive content sequencing, embedded learning analytics, and personalised feedback to enhance learning experiences in ODL environments. The prototype was developed using a Design Science Research (DSR) approach combined with Instructional Design-Based Development (IDD) and evaluated through a pilot study involving 40 postgraduate ODL course learners. The findings indicate that learners using the AI-enabled SIM achieved higher post-test scores than those using conventional SIMs (78.5% vs. 70.8%; Cohen's d = 0.65), with greater normalised learning gains (48.2% vs. 32.2%), an 18% increase in learning engagement, and an overall satisfaction score of 4.23 out of 5. In addition, the embedded early-warning model predicted dropout risk with 82% accuracy (AUC = 0.81), enabling timely instructor intervention that eliminated actual dropout among learners in the treatment group. These findings demonstrate that integrating adaptive learning, learning analytics, and AI-enabled feedback into conventional SIMs can substantially enhance learner engagement, academic performance, and retention while supporting the flexible learning aspirations of MQF 2.0.

*Corresponding author. E-mail address: noraini763@uitm.edu.my

1. INTRODUCTION

Open and Distance Learning (ODL) has become an increasingly important mode of higher education, offering learners greater flexibility to pursue their studies regardless of geographical location or personal commitments. In Malaysia, this shift reflects broader national efforts to widen participation in higher education while supporting lifelong learning and more flexible educational pathways. These aspirations are further reinforced by the Malaysian Qualifications Framework 2.0 (MQF 2.0), which promotes outcome-based education, seamless credit recognition, and the development of holistic competencies across both academic and Technical and Vocational Education and Training (TVET) sectors.

In most ODL environments, Self-Instructional Materials (SIMs) remain the primary medium for delivering learning content. These materials are commonly presented as printed notes, PDF documents, presentation slides, or recorded lectures that learners complete independently. While such resources provide flexibility, they are generally designed using a one-size-fits-all approach and offer little support for learners with different levels of prior knowledge, learning pace, motivation, or academic readiness. This limitation becomes increasingly significant in the context of MQF 2.0, which encourages higher education institutions to provide flexible, learner-centred educational experiences that accommodate diverse learning pathways (MQF, 2024). As learner diversity continues to increase, the ability of SIMs to adapt to individual learning needs is no longer an added advantage but an essential requirement for effective ODL delivery. However, conventional SIMs remain largely static, offering little opportunity to personalise learning experiences, provide timely feedback, or identify learners who require early academic support. Consequently, there is an increasing need to transform traditional SIMs into more adaptive, responsive, and data-informed learning environments.

Recent advances in Artificial Intelligence (AI) offer promising opportunities to address many of these limitations. Within the field of Artificial Intelligence in Education (AIED), AI has been widely applied to support adaptive learning, intelligent tutoring, open learner modelling, learning analytics, and personalised feedback (Shabalala, 2024). Rather than functioning solely as static learning resources, AI-enhanced SIMs can respond dynamically to learner performance, recommend personalised learning pathways, and provide timely instructional support throughout the learning process (Conati et al., 2018). Recent systematic reviews further indicate that AI applications in online and distance education are increasingly focused on adaptive learning, automated assessment, predictive analytics, and learner behaviour modelling, highlighting the growing maturity of AI-supported educational environments (Dogan et al., 2024).

Although previous studies have demonstrated the potential of AI to enhance adaptive learning, intelligent tutoring, learning analytics, and automated feedback, most of these technologies have been investigated as standalone educational applications rather than as integrated components of SIMs used in ODL. Existing studies also tend to focus on improving a single aspect of learning, such as personalisation, assessment, or learner analytics, with limited attention given to how these capabilities can be systematically combined within a unified SIM framework that aligns with institutional quality frameworks such as MQF 2.0. Consequently, there remains a need for a comprehensive AI-enabled SIM framework that not only supports personalised learning but also provides continuous learner monitoring, timely instructional intervention, and evidence-based quality improvement within flexible ODL environments.

To address this gap, the present study investigates how AI can be integrated into the design and delivery of SIMs for ODL. Specifically, the study presents the design, development, and evaluation of an AI-enabled SIM prototype that integrates adaptive content sequencing, embedded learning analytics, personalised feedback, and early-warning capabilities within a single learning environment aligned with the aspirations of the MQF 2.0. By combining these capabilities into a unified framework, the study seeks to demonstrate how AI can enhance learner engagement, improve academic achievement, support timely instructional intervention, and strengthen continuous quality improvement in ODL. The remainder of this paper is organised as follows. Section 2 describes the research methodology; Section 3 presents the prototype architecture and system features; Section 4 discusses the findings from the pilot implementation; and Section 5 concludes the paper.

2. RESEARCH METHODOLOGY

2.1 Research Design

This study employed the Design Science Research (DSR) methodology to guide the design, development, and evaluation of an AI-enabled Self-Instructional Materials (SIMs) framework for Open and Distance Learning (ODL). DSR is widely recognised as an appropriate research methodology for addressing complex educational and organisational problems by developing and systematically evaluating innovative solutions (Hevner et al., 2004; Peffers et al., 2007). Unlike conventional empirical approaches that primarily seek to explain existing phenomena, DSR focuses on developing practical solutions to identified problems while simultaneously contributing new knowledge to the field. The primary objective of this study was not merely to develop a technological application, but to propose an AI-enabled framework to enhance the effectiveness of SIMs in flexible ODL environments. To achieve this objective, the DSR methodology provided a systematic process for identifying existing challenges, translating educational requirements into design specifications, developing the proposed AI-enabled SIMs, and evaluating their effectiveness through iterative refinement. Recognising that effective educational technology must be grounded in sound instructional practice, the DSR process was complemented by the Instructional Design and Development (IDD) approach. Integrating these two methodologies ensured that both pedagogical and technological considerations were addressed throughout the development process. While DSR guided the overall research process and solution development, IDD provided a structured approach for aligning learning outcomes, instructional strategies, learner engagement, assessment activities, and AI-supported functionalities with the learner-centred principles advocated by the MQF 2.0 (Malaysian Qualifications Agency [MQA], 2024). As illustrated in Fig. 1, the research followed five iterative phases: (i) needs analysis, (ii) framework and instructional design, (iii) AI-SIM development, (iv) prototype implementation, and (v) evaluation. Each phase informed the subsequent stage, allowing continuous refinement of both the instructional design and the AI-enabled functionalities based on empirical evidence gathered throughout the study.

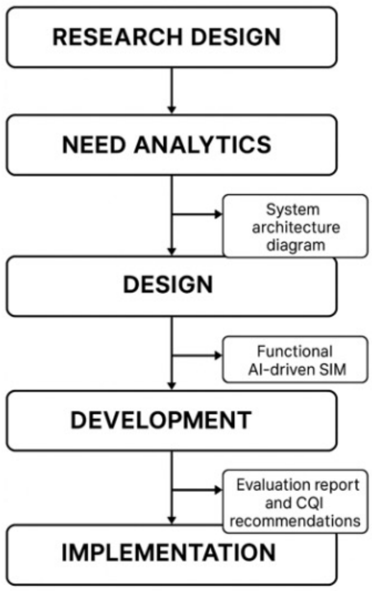

Fig.1 *Instructional Design-based Methodology Approach*
Source: Author (2026)

2.2 Needs Analysis

A multi-source data collection strategy was employed to identify performance gaps in current SIMs, consisting of three sources:

i. Institutional reports and course evaluation records, reviewed for patterns in completion and assessment performance.
ii. Surveys completed by students and instructors, asking specifically about content difficulty, how interactive the materials felt, and where self-paced learning tended to break down.
iii. Engagement logs from the LMS, which gave concrete numbers on time-on-task, where learners were dropping out of modules, and how quiz performance varied across material types.

We measured engagement rate (ER) as the ratio of active interaction time to total logged-in time (Eq. 1).

ER=T_active/T_total ×100 (1)
where T_active= active interaction time, T_total= total logged-in time.

The outcomes of the needs analysis established the foundation for the subsequent framework design phase, ensuring that every instructional and technological component incorporated into the proposed AI-enabled SIM addressed clearly identified educational needs rather than perceived technological opportunities.

2.3 Design

The instructional design followed the ADDIE model (Analyse, Design, Develop, Implement, Evaluate), which kept learning outcomes, cognitive levels, and assessment tasks aligned throughout (Molenda, 2015). The technical architecture translated those pedagogical decisions into three modules: (i) an Adaptive Content Sequencing Engine, (ii) an Embedded Analytics Dashboard, (iii) a Personalised Feedback and (iv) an Alerts Module. Each module had a defined role, and the three together formed a closed loop. The adaptive sequencing rule was straightforward: if a learner scored below 60% on the pre-assessment, they went to the remedial path (M_r); otherwise, they continued on the main path (M_n), as shown in Eq. 2.

$$\boldsymbol{f(x)} = \begin{cases} \boldsymbol{M_r} & \text{if } \boldsymbol{S_{pre} < 0.6} \\ \boldsymbol{M_n} & \text{if } \boldsymbol{S_{pre} \geq 0.6} \end{cases}$$

2.4 Development

The development process focused on ensuring that each AI-supported capability could be integrated seamlessly into the existing SIMs without disrupting established teaching and learning practices within Open and Distance Learning (ODL). The proposed AI-enabled SIM was developed by translating the identified instructional requirements into a functional learning environment. The AI-enabled SIM was developed using a modular architecture to facilitate future enhancement, maintenance, and scalability. The platform integrates conventional learning resources with several intelligent learning components, including adaptive content sequencing, AI-assisted personalised feedback, embedded learning analytics, and an early-warning mechanism. Rather than functioning as separate modules, these components operate collectively to provide continuous learner support throughout the learning process.

The dropout risk model used logistic regression with three predictors: engagement rate (x_1), assessment score (x_2), and inactivity duration (x_3), as shown in Eq. 3. The model produces a probability estimate, P(d), for each learner, which feeds directly into the alert system. The process involved:

- Develop text, multimedia, quizzes, and feedback scripts.
- Build or embed AI modules using Python (e.g., scikit-learn, TensorFlow) for prediction, clustering, or recommendation.
- Connect SIM to LMS via APIs for data capture. Pilot-test modules iteratively and debug adaptivity functions.

Predictive model for dropout risk monitoring as in Eq. 3:

$$P(d) = 1 / (1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3)}) \quad (3)$$

where P(d) = probability of dropout, x_1 = engagement rate, x_2 = assessment score, x_3 = inactivity duration, and βs are model coefficients estimated from training data.

2.5 Implementation

The development process for Deployment involved enrolling learners, conducting an orientation session, and continuously monitoring engagement, progress, and satisfaction via the analytics layer. When a learner's dropout probability exceeded the defined threshold, the system sent an alert to the instructor. Two implementation metrics tracked the system's performance in use: completion rate (CR, Eq. 4) and average feedback latency (AFL, Eq. 5).

$$CR = (N\_completed / N\_enrolled) \times 100 \quad (4)$$

$$AFL = [\sum(t\_response,i - t\_request,i)] / n \quad (5)$$

2.6 Evaluation

Evaluation compared pre- and post-test scores, collected satisfaction ratings via a Likert-scale survey, and gathered instructor perspectives through interviews. We measured learning gain using Hake's normalised gain formula (Eq. 6), which controls for differences in pre-test performance and avoids ceiling effects. Overall system quality was tracked using the Quality Improvement Index (QII, Eq. 7), which averages changes in completion rate, learning gain, and satisfaction score across design iterations. A positive QII means the system improved.

$$LG = [(S\_post - S\_pre) / (100 - S\_pre)] \times 100 \quad (6)$$

$$QII = [(CR\_new - CR\_old) + (LG\_new - LG\_old) + (SS\_new - SS\_old)] / 3 \quad (7)$$

A positive QII indicates improvement after system refinement. The subsequent section presents the prototype architecture and features, followed by empirical findings derived from the pilot implementation.

3. PROTOTYPE ARCHITECTURE AND FEATURES

The AI-enable SIM prototype was built on a four-layer architecture: (1) Presentation/UI layer: learner, instructor, and administrator views; (2) Learner Model layer: knowledge state, engagement profile, and prior assessment results; (3) Adaptation/AI Engine layer: content sequencing logic and predictive dropout models; and (4) Data layer: interaction logs and content repository. This decomposition follows the established Adaptive Learning System (ALS) component model comprising Learner Model, Adaptation Model, and Content Model (Wang et al., 2024).

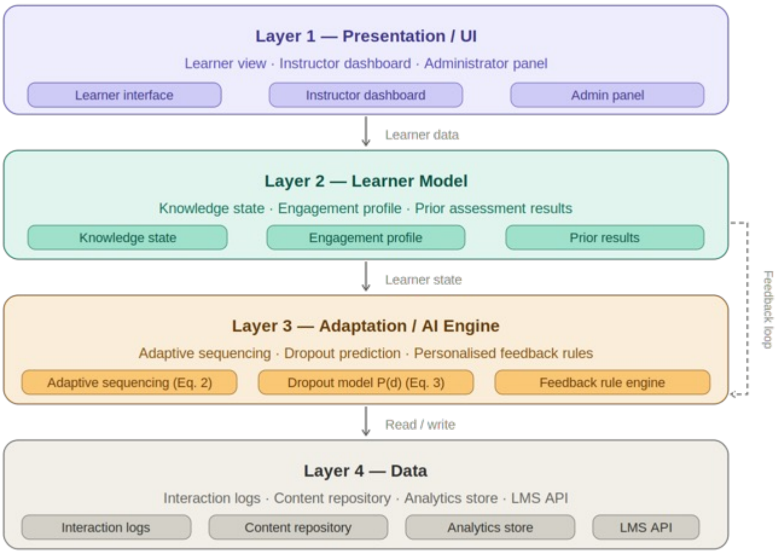

Fig.2 *Four-Layer System Architecture of the AI-enabled SIM Prototype*
Source: Author (2026)

The adaptive loop is what ties it together. A learner interacts with content; that interaction updates the learner model. The system then makes a new sequencing decision, delivers the next content unit, updates the analytics, and either provides feedback or triggers an alert. The loop runs continuously throughout a session. Each of the three modules plays a distinct role in that loop:

i. Adaptive Content Sequencing routes learners based on diagnostic results and ongoing performance data. Below 60% on a pre-assessment means the remedial path; 60% or above means the main path. Lightweight decision rules handle most routing decisions, with machine learning models supporting more complex cases.
ii. The Embedded Analytics Dashboard captures time spent, error frequency, module completions, and idle periods, displaying them in real time to both learners and instructors. The dashboard uses a self-comparison reference frame, so learners see their own trajectory rather than their rank within the class. This design choice deliberately supports self-regulated learning behaviour.
iii. Personalised Feedback and Alerts deliver in-moment hints when a learner is stuck, periodic progress summaries, and instructor alerts when the dropout model calculates that P(d) has crossed the intervention threshold.

Table 1 illustrates how each module aligns with the five fundamental SIM quality criteria established by Rowntree (1990): (1) self-explanatory, (2) self-directed, (3) self-contained, (4) self-motivating, and (5) self-evaluating, while highlighting the corresponding AI mechanisms, learner support functions, and instructor facilitation roles. By explicitly demonstrating the extent to which AI enhances or substitutes traditional SIM functions, the framework offers a theoretical basis for explaining the evolving nature of ODL delivery.

SIM Quality Criteria	Module	AI Mechanism	Learner Function Supported	Instructor Function
Self-Explanatory	Adaptive Content Sequencing	Diagnostic pre-assessment + decision-rule path selection	Understand content at one's own level	Curriculum mapping
Self-Directed	Adaptive Content Sequencing	Bayesian Knowledge Tracing / rule-based remediation (M_r if $S_{pr}^{e} < 0.6$)	Learner controls pace & pathway	Pathway design
Self-Contained	Embedded Analytics Dashboard	Descriptive & predictive analytics (engagement rate, mastery tracker)	Monitor own progress visually	At-risk monitoring
Self-Motivating	Personalised Feedback & Alerts	Logistic regression dropout model P(d); threshold-based instructor alerts	Receive timely hints & encouragement	Proactive intervention
Self-Evaluating	Personalised Feedback & Alerts	Automated formative feedback + QII = (CR + LG + SS) / 3	Reflect on knowledge gaps	CQI decisions

Table 1 *AI-SIM Feature Taxonomy: Mapping Modules to SIM Quality Criteria*

Table 2 positions the prototype against static SIMs, generic LMS dashboards, and intelligent tutoring systems across six dimensions. The prototype is the only system in the comparison that meets all five SIM quality criteria.

Feature	Static SIM	Generic LMS Dashboard	Intelligent Tutoring System (ITS)	This Prototype (AI-SIM)
Adaptivity Type	None	None	ML/Rule-based	Rule-based + logistic regression
Analytics	None	Descriptive only	Descriptive + predictive	Descriptive + predictive + prescriptive
Feedback Type	Static	Aggregated	Intelligent, immediate	Personalised, in-moment + periodic summary
At-Risk Prediction	No	No	Limited	Yes (82% accuracy, AUC = 0.81)
ODL Deployment Context	Yes	Partial	Rarely	Yes (MQF 2.0 aligned)
SIM Quality Criteria Met	1/5	2/5	3/5	5/5

Table 2 *Comparison of AI-SIM Prototype Against Existing Systems*

3.1 Data Collection and Instruments

- Learning analytics logs: timestamps, clickstreams, module transitions, hint requests, error counts, dwell time per screen.
- Pre- and post-tests: multiple choice and short answers assessing comprehension.
- Survey instrument: Likert scale items (1–5) on satisfaction, motivation, and perceived adaptivity.
- Interview protocol: open questions on user experience, perceived benefits, challenges, and suggestions.

3.2 Data Analysis

- Quantitative analysis: Paired t-tests (pre vs post within groups), independent t-tests (between groups), effect sizes (Cohen's d), and Hake's normalised gain <g>. Regression models examined which analytics metrics predicted post-test gains.
- Qualitative analysis: Thematic coding of interview transcripts to identify common themes (usability, adaptation, autonomy, instructor role).
- Dropout risk modelling: Logistic regression using early behavioural data, evaluated via confusion matrix, ROC/AUC, and F1-score.

4. RESULTS AND DISCUSSION

This section presents findings from the pilot implementation of the AI-SIM prototype with 40 postgraduate ODL learners (treatment group n = 20; control group n = 20). Data were collected through system logs, embedded analytics, and learner surveys. Results are discussed across three dimensions: (i) learner engagement and usage patterns, (ii) learning gains and comprehension, and (iii) learner satisfaction, motivation, and perceptions. A fourth dimension addresses dropout risk prediction and its practical implications, as shown in the figure. 3 below.

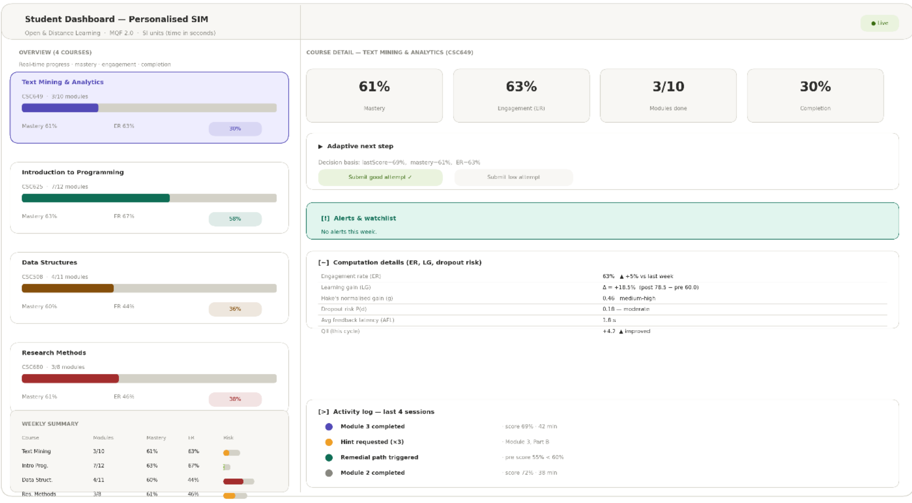

Fig. 3 *Prototype Dashboard Interface Showing Learner Progress Across Four Courses*
Source: Author (2026)

4.1 Learner Engagement and Usage Patterns

The most immediate difference between the two groups was how they navigated the material. Control-group learners moved through modules in a straight line and tended to stop when a session ended. Treatment-group learners behaved differently. About 25% of their activity involved returning to supplementary explanations or stepping into remedial content, suggesting they were responding to what the system showed them rather than just working through a fixed sequence.

Total time in the learning environment was also higher for the treatment group: an average of 45 hours (SD = 6.2) against 37.5 hours (SD = 7.1) for the control group ($p < 0.05$). More interesting than the total is the shape of that engagement over time. Fig. 4 shows engagement rates week by week across the eight-week study period. The treatment group kept climbing through Week 6, then held steady. The control group levelled off after Week 3. That kind of sustained engagement is consistent with findings from other studies in adaptive e-learning environments, where real-time feedback keeps learners active in ways that static materials do not (Torras & Saura, 2022). The dashboard seems to have encouraged learners to monitor their own progress, a pattern associated with self-regulated learning (Zimmerman, 2002).

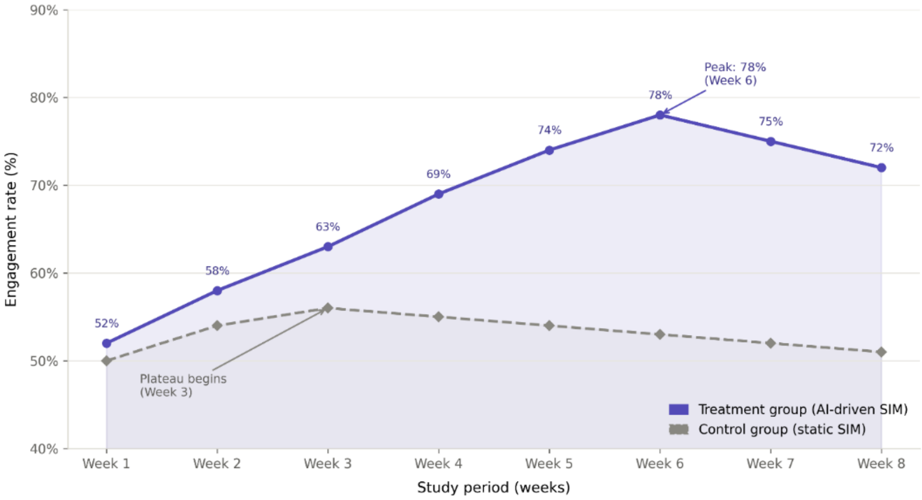

Fig. 4 *Weekly Engagement Learning Curve: Treatment vs Control Group*
Source: Author (2026)

4.2 Learning Gains and Comprehension

Table 3 shows that the treatment group's mean post-test score was 78.5% (SD = 9.1), compared with 70.8% (SD = 10.8) for the control group. The difference was statistically significant ($t = 2.47$, $p = 0.016$) with a moderate-to-large effect size ($d = 0.65$, 95% CI [0.03, 1.26]). Hake's normalised gain tells a clearer story than raw percentages, because it accounts for how much room each group had to improve. The treatment group's normalised gain was 0.482 (medium-high), the control group's was 0.322 (medium). That gap reflects a real difference in how effectively the two groups converted study time into knowledge.

Regression analysis found that three dashboard-tracked variables jointly explained 52% of the variance in post-test scores ($R^2 = 0.52$, $p < 0.001$): how often learners requested hints, how much their dwell time varied across content units, and their module completion rate. The dashboard metrics were not just monitoring outputs; they were tracking the behaviours that actually drove learning.

Group	Pre-test Mean (SD)	Post-test Mean (SD)	Gain (%)	p-value
Treatment	58.3% (10.2)	78.5% (9.1)	+20.2%	< 0.001
Control	56.9% (11.5)	70.8% (10.8)	+13.9%	< 0.001
Hake's Normalised Gain <g>	—	—	0.482 (medium-high)	—

Source: Authors. Note: Hake's normalised gain <g> = (post − pre) / (100 − pre). Effect sizes interpreted per Cohen (1988): small d = 0.2, medium d = 0.5, large d = 0.8.

Table 3 *Summary of Learning Gains and Comprehension*

Table 4 places $d = 0.65$ in context against four published meta-analyses. The figure sits within the range reported for adaptive learning systems generally (Wang et al., 2024, $g = 0.70$), intelligent tutoring systems specifically (Kulik & Fletcher, 2016, $g = 0.62$; Ma et al., 2014, $g = 0.44$ to 0.58), and AI-assisted learning tools including ChatGPT (Liu et al., 2025, $g = 0.577$). The prototype's effect size is competitive with that of purpose-built intelligent tutoring systems, despite operating within an ODL infrastructure rather than a controlled lab setting.

Study / Meta-Analysis	Context	Effect Size	Source
This Study	AI-enabled SIM, ODL	d ≈ 0.65	—
Wang et al. (2024).	Adaptive Learning Systems (45 studies)	g = 0.70	J. Educ. Computing Research
Kulik & Fletcher (2016).	Intelligent Tutoring Systems (50 studies)	g ≈ 0.62	Review of Educ. Research
Ma et al. (2014).	ITS vs human instruction (107 effects)	g = 0.44–0.58	J. Educational Psychology
Liu et al. (2025).	ChatGPT on achievement (37 studies)	g = 0.577	J. Computer Assisted Learning

Source: Authors, compiled from Wang et al. (2024); Kulik & Fletcher (2016); Ma et al. (2014); and Liu et al. (2025).

Table 4 *Effect Size Benchmarks: AI-SIM vs Published Meta-Analytic Evidence*

4.3 Learner Satisfaction, Motivation, and Perceptions

Treatment-group learners rated overall satisfaction at 4.23 (SD = 0.72) out of 5, compared with 3.56 (SD = 0.81) in the control group ($p < 0.01$). Across all five survey items, the treatment group averaged above 4.0, with very few negative or neutral responses. Table 5 shows the full distribution.

Satisfaction Item	SD (%)	D (%)	N (%)	A (%)	SA (%)	Mean	SD	n
Adaptivity of content	0	2.5	10.0	52.5	35.0	4.20	0.76	40
Clarity of personalised feedback	0	0	7.5	55.0	37.5	4.30	0.65	40
Usefulness of the analytics dashboard	0	5.0	12.5	47.5	35.0	4.13	0.82	40
Perceived intelligence of the system	0	2.5	15.0	50.0	32.5	4.13	0.77	40
Overall satisfaction	0	2.5	10.0	50.0	37.5	4.23	0.72	40
Note: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree. Likert scale 1–5.	**Overall: M = 4.23, SD = 0.72**							

Table 4 *Satisfaction Survey: Full Likert Response Distribution (Treatment Group, n = 40)*

As shown in Table 5, all items had mean scores above 4.0/5, with a few neutral responses and negligible negative responses. Learners in qualitative interviews particularly appreciated the immediacy of hints and the visual mastery indicators. One participant remarked: “The dashboard made me realise when I was falling behind, it felt like having a personal coach.” These perceptions align with Keller’s ARCS motivational model (Attention, Relevance, Confidence, Satisfaction), in which timely and personalised feedback enhances persistence (Keller, 2010).

4.4 Dropout Risk Prediction and Timely Intervention

Using behavioural data from the first three weeks, a logistic regression model predicted dropout with 82% accuracy. However, to address the limitations of accuracy under potential class imbalance, full diagnostic metrics were computed. Table 6 presents the complete dropout prediction performance alongside published benchmarks.

Metric	Treatment Group	Control Group	Benchmark (OU, 2024)	Benchmark (SentiDrop, 2025)
Accuracy	82%	N/A	91%	84%
AUC-ROC	0.81	N/A	0.913	0.85*
Precision	0.79	N/A	—	—
Recall (Sensitivity)	0.84	N/A	—	—
F1-Score	0.81	N/A	—	—

Source: Authors. Benchmarks: Open University dropout model (ACM MLMI, 2024); SentiDrop (arXiv:2507.10421, 2025 preprint). *Estimated from reported performance metrics.

Table 6 *Dropout Prediction Model Performance and Benchmarks*

The model achieved AUC = 0.81 and F1-score = 0.81, with a recall of 0.84, indicating strong sensitivity to at-risk learners, where the metric is most critical for timely intervention. In the treatment group, the system flagged eight at-risk learners; six received synchronous instructor interventions via dashboard alerts, and all six subsequently completed the module. In the control group, five learners discontinued participation. This supports the hypothesis that real-time monitoring combined with instructor alerts reduces actual dropout in ODL settings (Dogan et al., 2024).

While the 82% accuracy and AUC = 0.81 are competitive with published distance-education dropout models (84–91%), the Open University XGBoost model (AUC = 0.913) demonstrates that further feature engineering and larger training datasets can improve predictive performance. Future iterations should incorporate sentiment analysis, social engagement features, and explainability mechanisms (SHAP values) to enhance administrator trust and model transparency.

4.5 Implications for Mqf 2.0 and Flexible Learning

The AI-enabled SIM prototype directly supports the three MQF 2.0 pillars that underpin ODL transformation: Values-Based Education (through ethics-aware adaptive pathways), Flexible Learning Pathways (through adaptive sequencing accommodating diverse paces and trajectories), and Continuous Quality Improvement (through the QII metric and analytics-driven design cycles). Deployment must, however, address institutional capacity, data privacy, AI transparency, instructor training, and learners' digital literacy, which are constraints consistently reported in AIED research (Dogan et al., 2024).

5. CONCLUSION

The findings from the pilot study provide empirical support for the effectiveness of the AI-enabled Self-Instructional Materials (SIM) prototype in enhancing learner engagement, comprehension, and satisfaction within Open and Distance Learning (ODL) environments. The integration of adaptive content sequencing, embedded analytics, and personalised feedback enabled learners to receive continuous, data-informed support. The treatment group achieved a normalised gain of $\langle g \rangle = 0.482$ and Cohen's d ≈ = 0.65, which is consistent with established meta-analytic benchmarks for adaptive learning systems (0.44–0.70). In contrast, the dropout prediction model achieved an AUC of 0.81 and zero actual dropouts in the treatment group.

Beyond instructional benefits, the prototype contributes to MQF 2.0 goals of Values-Based Education, Flexible Learning Pathways, and Continuous Quality Improvement. The SIM quality criteria taxonomy presented in Table 2 offers a reusable framework for designing AI-enabled SIMs in any ODL context. Future research should examine scalability across disciplines, long-term learning retention, and the ethical integration of AI. Institutional adoption will require policies addressing data ethics, AI transparency, and digital readiness.

6. ACKNOWLEDGEMENTS

The authors acknowledge the financial support provided by Universiti Teknologi MARA (UiTM) for the publication of this article.

7. FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

8. AUTHORS' CONTRIBUTIONS

Noraini Seman: Conceptualisation, methodology, formal analysis, investigation, writing original draft, and project administration. Norjansalika Janom: Methodology, validation, writing review and editing, and supervision. Prasanna Ramakrisnan: Formal analysis, software development, data curation, writing, review and editing.

9. CONFLICT OF INTEREST DECLARATION

We certify that the article is the Authors' and Co-Authors' original work. The article has not received prior publication and is not under consideration for publication elsewhere. This research/manuscript has not been submitted for publication, nor has it been published in whole or in part elsewhere. We attest that all Authors have contributed significantly to the work, the validity and legitimacy of the data, and the interpretation of the data for submission to IJELHE.

10. DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

During the preparation of this work, the authors incorporated generative AI-assisted programming tools to support rapid prototyping, code refinement, interface design, and debugging during the development of the proposed AI-enabled Self-Instructional Material (AI-SIM). These tools were used solely as development aids. All software architecture, functional requirements, system integration, testing, validation, and the final implementation were designed, reviewed, and verified by the authors, who take full responsibility for the content of this publication.

11. DATA AVAILABILITY

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

12. REFERENCES

Conati, C., Porayska-Pomsta, K., & Mavrikis, M. (2018). AI in Education Needs Interpretable Machine Learning: Lessons from Open Learner Modelling. arXiv preprint. https://doi.org/10.48550/arXiv.1807.00154

Dogan, M. E., et al. (2023). The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. Applied Sciences, 13(5). https://doi.org/10.3390/app13053056

Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. American Journal of Physics, 66(1), 64–74. https://doi.org/10.1119/1.18809

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. MIS Quarterly, 28(1), 75–105. https://doi.org/10.2307/25148625

Keller, J. M. (2010). Motivational design for learning and performance: The ARCS model approach. Springer. https://doi.org/10.1007/978-1-4419-1250-3

Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. Review of Educational Research, 86(1), 42–78. https://doi.org/10.3102/0034654315581420

Liu, J., et al. (2025). The impact of ChatGPT on students' academic achievement: A meta-analysis. Journal of Computer Assisted Learning, 41(3). https://doi.org/10.1111/jcal.70096

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. Journal of Educational Psychology, 106(4), 901–918. https://doi.org/10.1037/a0037123

Malaysian Qualifications Agency. (2024). Malaysian Qualifications Framework (MQF) 2.0 (2nd ed.). MQA.

Molenda, M. (2015). In search of the elusive ADDIE model. Performance Improvement, 54(2), 40–42. https://doi.org/10.1002/pfi.21461

Panwale, S. B., et al. (2025). Evaluating AI-personalised learning interventions. International Review of Research in Open and Distributed Learning. https://doi.org/10.19173/irrodl.v26i1.7813

Rowntree, D. (1990). Teaching through self-instruction: How to develop open learning materials. Kogan Page.

Shabalala, N. P. (2024). Elevating STEM learning: Unleashing the power of AI in Open Distance eLearning. Research in Social Sciences and Technology, 9(3), 269–288. https://doi.org/10.46303/ressat.2024.59

Wang, X., Huang, R., Sommer, M., Pei, B., Shidfar, P., Rehman, M. S., Ritzhaupt, A. D., & Martin, F. (2024). The efficacy of artificial intelligence-enabled adaptive learning systems from 2010 to 2022 on learner outcomes: A meta-analysis. Journal of Educational Computing Research, 62(6). https://doi.org/10.1177/07356331241240459

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. Theory into Practice, 41(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2