SMART-OU: Smart Model for AI-Enabled Remote Teaching in Open Universities

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Abstract

Open Universities (OUs) are characterized by large-scale distance education, diverse learner profiles, and flexible temporal arrangements; however, remote teaching still suffers from low engagement, delayed feedback, limited personalization, heavy teaching loads, and other inequities. This concern has led to the design of an OU-specific smart model for AI-enabled Remote Teaching (SMART-OU) based on a progressive approach to teaching and learning, in which instruction, practice, feedback, and assessment are tailored to support small, incremental mastery. SMART-OU uses learning analytics, AI-enabled content scaffolding, formative assessment, and ethical design and implementation as its foundational pillars. The model prescribes and delineates a learner journey along the stages of the learning process: diagnose, scaffold, practice, assess, support, and an instructor's journey through the design, monitoring, intervention, and improvement stages, all supported by AI tools: adaptive sequencing, automated feedback, risk prediction, and learning assistant chat. This paper outlines the model's key elements, data flow, evaluation, resource allocation, and implementation for OUs and other institutions of higher education. The model aims to optimize retention and provide timely intervention for at-risk learners, achieve greater consistency across diverse cohorts, and significantly reduce administrative workload, all while safeguarding the core values of academic integrity, inclusiveness, and transparency.

Keywords: Open Universities, Artificial Intelligence in Education, Remote Teaching, Distance Learning, Learning Analytics, Academic Integrity.

Introduction

Among the various providers of higher education, open universities and open distance learning institutions are particularly important for working adults, mainly in rural areas, and other non-traditional learners, and are present in every part of the world. These institutions have a mission of accessibility, flexibility, and scalability (Cao et al., 2025). However, open universities face challenges in remote teaching due to rapid advances in artificial intelligence in education, among others. Research shows (Ashfaq et al., 2024) that these include delayed feedback, limited learner-instructor interaction, large learner cohorts resulting in increased dropout rates, and increased teaching workload. Deploying still remains an unresolved challenge.

Most artificial intelligence technologies positively impact educational processes through personalized learning, automated feedback, early warning systems for high-risk learners, and increased, on-demand learner support. Unfortunately, most educational AI teaching models fail to meet the teaching and
learning, structural, pedagogical, and ethical challenges that are particularly present in open and remote universities. Studies (Fabriz et al., 2021) have shown that students in open-learning

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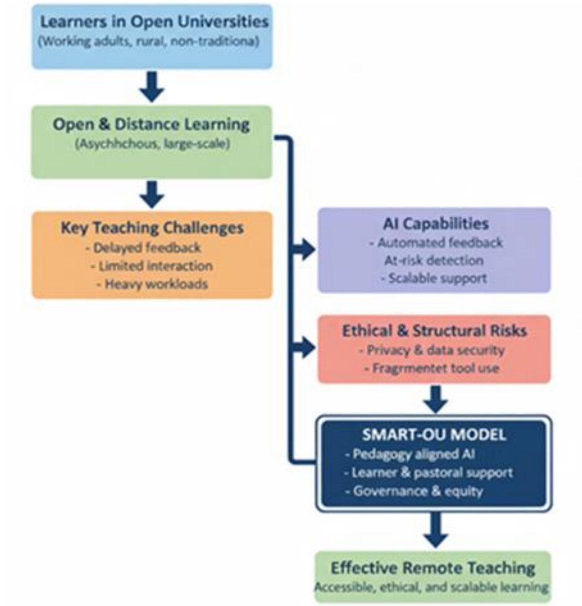
contexts usually study asynchronously, have inconsistent internet access, and need solid academic and pastoral care support. Furthermore, in large-scale, remote contexts, concerns about data privacy, algorithmic discrimination, and academic dishonesty increase. In the absence of a coherent institutional model, the adoption of AI risks becoming piecemeal, instrumentally focused, and out of sync with AI's educational purpose.

This paper presents the acronym SMART-OU, which stands for a Smart Model for AI-Enabled Remote Teaching in Open Universities. The model describes how AI technologies can be integrated to support open learning. The model attempts to integrate pedagogy, learner support systems, assessment integrity, and administrative frameworks. This paper will highlight SMARTOU, its conceptual foundations, the design and mechanisms that underpin it, and its potential to advance research in open universities. Figure 1 presents a conceptual flow of SMART-OU.

Figure 1: Flow Diagram of SMART-OU



The research addresses the following questions:

1. What are the essential elements necessary for an effective model of AI-enabled remote teaching in open universities?
2. How can AI be addressed in the teaching and support activities in a manner that is equitable and protects privacy and academic integrity?
3. In large-scale open learning, how can the effectiveness of such a model be determined?

Literature Review

This part addresses the theoretical and empirical foundations of AI-enabled remote teaching in open universities. This research integrates studies focusing on open and distance learning; educational artificial intelligence; learning analytics; assessment integrity; and ethics, and governance. By framing the current study within the existing literature, this chapter illuminates past research findings, ongoing challenges, and gaps that suggest the need for the SMART-OU model.

Open Universities and Remote Teaching

The literature (Nascimento et al. 2022) suggests open universities were designed to facilitate access to higher education by addressing age, geographical, prior qualifications, and employment barriers, predominantly through technology-mediated open and distance learning. Research (Hale & Frank, 2023) indicates that these institutions attract numerous learners and cater to diverse student demographics; thus, there is a need to incorporate flexible, asynchronous, and self-directed learning. Yet, prior research consistently identifies learner support, interaction, and timely feedback as critical to student success. The ability of individuals to participate meaningfully in these systems and frameworks has consistently been identified as an ongoing concern (Azizi & Bashirian). The gaps in meaningful engagement generate intermediary concerns about system feedback among participants. These gaps create relational and interactive voids among system users, which in turn generate and perpetuate low system retention and completion rates. Remote learning obstructions, systems, and processes were identified and investigated in detail to provide a concise 'go to' reference for other users.

Table 1: Key Issues in Open Universities & Remote Teaching

Issues in Current Open Universities	Description
Limited Technological Infrastructure(Adsız & Dinçer, 2025)	Inadequate internet access, outdated learning management systems, and lack of digital resources affect effective remote teaching
Quality of Instruction (Xu, 2025)	Dependence on standardized and recorded materials can reduce instructional depth and limit interactive learning
Student Engagement(Calleo & Pilla, 2025)	Minimal real-time interaction leads to lower participation, weak peer collaboration, and higher dropout rates
Delayed Feedback (Kalmar et al., 2022)	Large student enrollments often cause delays in grading and feedback, reducing learning effectiveness
Limited Personalization (Thelma et al., 2024)	Courses are usually designed for mass delivery, making it difficult to address individual learning needs
High Instructor Workload (Zito et al., 2024)	Faculty members handle large classes, content creation, and online support, increasing workload and stress

Artificial Intelligence in Education

Artificial Intelligence (Kenchakkanavar, 2023) and education were described and defined as Computer systems and processes capable of conducting interrelated system functions characteristic of and inclusive of human intelligence. Educational systems have incorporated supports for AI-embraced learning and system instruction to strengthen organizational educational frameworks (Xu, 2025). Personalized education and the accessibility of educational facilities were noted and highlighted within the scope of organizational educational processes. (Yadav & Shrawankar, 2025) argued that educational systems and processes have incorporated supports of AI, embraced learning and system instruction to support system and process organizational educational frameworks.

Learning Analytics and Student Retention

Angeioplastis et al. (2025) defines learning analytics as the systematic collection and analysis of learner data to improve educational outcomes. Learning analytics is considered one of the strategies to address student retention in open and distance learning. Analytics help institutions to detect patterns pertaining to persistence and support retention strategies based on evidence (Adlof et al., 2023).

Learning Analytics and Early Warning Systems: The literature (Kustitskaya et al., 2022) reports the application of learning analytics to early warning systems designed to flag students as at risk based on criteria such as engagement and submissions. Research shows that at-risk students who are identified early and receive academic or advisory support are more likely to be retained.

Limitations of Engagement Metrics: Scholars (Shtaleva et al., 2020) caution against overreliance on behavioral indicators as measures of engagement. In distance education settings, diverse learning behaviors and limited internet access may lead to inaccurate risk classifications.

Ethical Considerations: The literature (Mathrani et al., 2021) highlights concerns from learning analytics, including privacy, transparency, and fairness. Particularly in open universities, the need for ethical frameworks to protect data about vulnerable learners is paramount, as is the need for ethical use of data.

Remote Assessment and Academic Integrity

The literature (Vellanki et al., 2023) characterizes academic integrity as a continually open issue in open and distance learning, particularly in remote assessment scenarios. Studies show that online assessments add a layer of misconduct, such as plagiarism and impersonation (Surahman et al., 2022), while traditional forms of monitoring have faced backlash over privacy and accessibility concerns. Newer research (Kovari, 2025) assesses various uses of AI to detect plagiarism and analyze assessment behavior, suggesting these systems may be valuable to instructors but cautioning that false positives are common and should not be relied on solely for punitive measures. As a result, there is a growing call for integrity-by-design approaches that emphasize authentic assessments that target higher-order thinking, with AI providing feedback and supervision while humans maintain control over decisive outcomes.

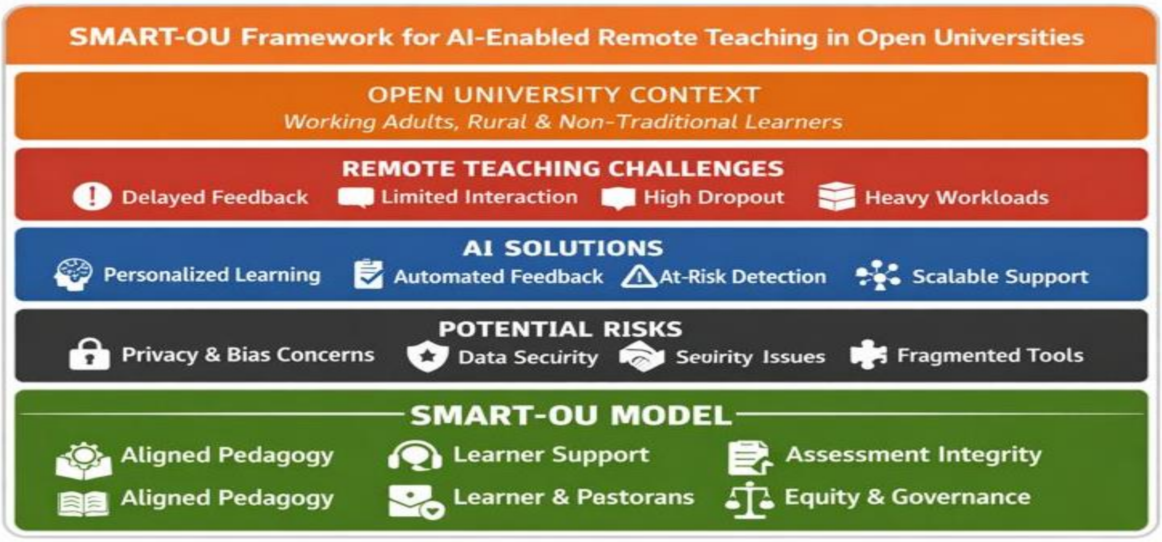
This work builds on the literature analysis focusing on Artificial Intelligence in distance and online learning/teaching. There still seems to be an emphasis on examining individual tools and their functionalities. There is still little to no attention to the entwined contextual models that aim to integrate AI to address pedagogy, students, assessment, and governance in open universities. There seems to be little attention to the dimension, multiplicity, and equity of the open and distance learning systems.

To fill this gap in intelligence systems, the research developed the SMART-OU model as an integrated framework of AI-driven education in open universities.

Proposed Smart-OU Framework

This part describes the SMART-OU framework as a gradually institutional model for the integration of artificial intelligence in distance teaching in open universities. Alignment of the Framework of pedagogy, equity, educational governance, and integrity ensures automation augments the role of the human in academic decision-making. Basic components of SMART-OU are illustrated in Figure 2.

Figure 2: Basic Components of SMART-OU



Design Principles

SMART-OU rests on and is sustained by five foundational tenets. First, the framework is pedagogy-driven, ensuring that the support of AI is for the achievement of learning outcomes as opposed to tool-led pedagogy than experiment. Second, human intervention is a necessity in any high consequences academic decision, more so in evaluation and progression (Wright, 2017). Third, the framework is driven by equity, accessibility, and inclusion in consideration of the varied circumstances of the Open University learners. Fourth, an integrity-by-design approach goes to assessment and the use of data. Finally, the framework is modular and scalable, thus, can be progressively adopted based on the readiness of the institution.

Core Framework Components

This part describes the essential components of the SMART-OU framework that support the AI-enabled distance teaching, while ensuring the pedagogical alignment, academic integrity, and human oversight.

Smart Learning Design: Aligning learning objectives, instructional methods, and assessments is at the core of the framework of Smart Learning Design. While instructors retain the autonomy of their content, AI tools provide support with content structuring, gap identification, readability and accessibility. This fosters uniform learning experiences within large and heterogeneous groups.

AI-Enabled Learning Services: AI-enabled services provide scalable learner support, including conversational assistants for course queries, adaptive resource recommendations, and rubric-aligned formative feedback. These services operate only on approved institutional content and function as supplements to instructor and tutor interaction, not replacements.

Learner Support and Learning Analytics: Learning analytics support the integration of engagement and performance data to flag learners that might need academic or pastoral assistance. A human-in-the-loop approach is applied (Nunes et al., 2015), where analytics outputs are interpreted by tutors and advisors to implement actions ensuring equitable and contextual intervention.

Assessment and Academic Integrity: Within SMART-OU, the assessment focuses on real, authentic application type assessments to mitigate the likelihood of academic dishonesty. AI tools provide assistance in checking for similarities, citation anomalies and spotting outliers. However, all concerns related to integrity are escalated to academic staff to guarantee fairness and due process.

Teaching Analytics and Continuous Improvement: Instructional and administrative teaching analytics provide data on student engagement, student progress and teaching load. These data then inform course enhancement, improved teaching methods, and better targeted teaching resource allocation.

Governance and Capacity Building: Governance frameworks determine the structures for ethical uses of AI, privacy of data, risk and compliance management, and policy adherence. Building Capacity develops AI literacy for faculty, tutors, and learners, tailoring the responsible use of systems. Issues facing the Open University and remote teaching are shown in Table 2.

Table 2: Key Issues in Open Universities & Remote Teaching

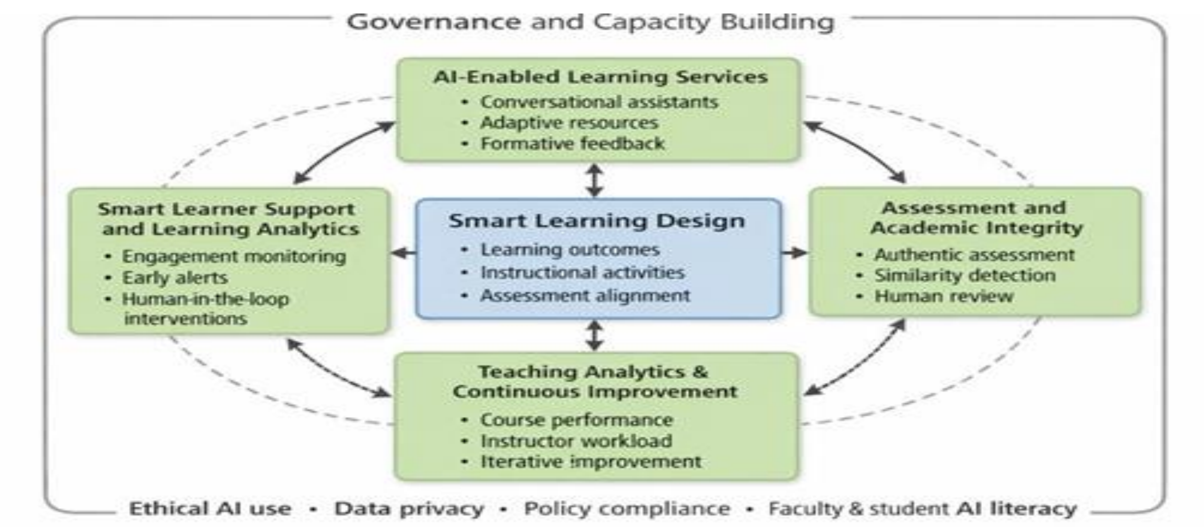
Section	Component	Description
Design Principles	Pedagogy, integrity, equity	AI use is outcome-driven, inclusive, and governed by human oversight.
Core Components	Learning design and services	AI supports course design and learner support under instructor control.
	Analytics and support	Analytics inform learner support through human interpretation.
	Assessment and governance	Authentic assessment, integrity checks, and ethical AI governance.

Framework Overview

Researchers can observe that the SMART-OU framework resembles a layered model (Gasser & Almeida, 2017). Smart learning design is the core layer surrounded by AI-enabled learning services, smart learner support, assessment, academic integrity, teaching analytics and continuous improvement. Having governance and capacity building for ethical oversight and institutional support encircle the framework. This design illustrates the core importance of pedagogy and the venue opening the governance in cross-cutting AI-based remote teaching. Figure 3 provides illustration of the SMART-OU framework on a layered model and shows interconnectedness. Smart learning design is the core of teaching and learning activities around which the framework is built.

Four operational components are situated around the core: AI-enabled learning services, smart learner support, assessment and academic integrity and teaching analytics and continuous improvement. These operational components interact in a manner to contribute to tailored pedagogical support for disengaged learners. Engaged learners will contribute to instructional effectiveness and accessible education. Governance and capacity building structures surrounding the framework provide ethical oversight, policy guidance and institutional support. This layered representation illustrates importance of pedagogy and the cross-cutting role of governance in remote teaching AI.

Figure 3: SMART-OU Framework for AI Remote Teaching



Operational work flows of Smart-OU

This section translates the SMART-OU framework into repeatable operational workflows that support scalable, integrity-aware remote teaching while preserving human authority.

Delivery Cycles

SMART-OU operates across three institutional cycles:

Pre-delivery: Course design, AI configuration, and governance controls
In-delivery: Live teaching, learner support, and assessment execution
Post-delivery: Evaluation, redesign, and policy refinement

This cyclical structure supports continuous improvement and prevents fragmented AI adoption.

Learner Workflow

The learner journey follows five structured stages:

Diagnose: Readiness profiling and pathway initialization
Scaffold: Adaptive content delivery aligned with learning outcomes
Practice: Low-stakes activities with rubric-based formative feedback
Assess: Integrity-aware summative assessment with human grading authority
Support: Analytics-informed academic and pastoral interventions

Artificial Intelligence provides personalization and forecasting, though the analysis and action still remain in the hands of the advisors and tutors.

Instructor and Course Team Workflow

Instructor workflows consist of four stages:

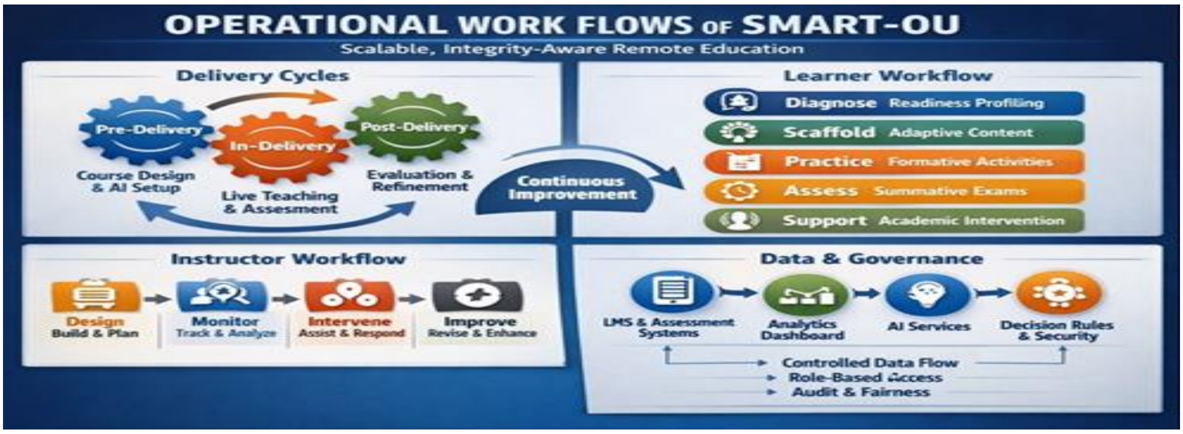
Design: development of micro-units, rubrics, and authentic assessments
Monitor: use of dashboards to track mastery, engagement, and risk
Intervene: tiered academic and advisory responses based on evidence
Improve: iterative refinement of content, assessments, and support rules

The results of the analysis are meant for assisting in decision making, rather than making the decision for you.

Data, Decision Rules, and Governance

SMART-OU relies on controlled data flows connecting the LMS, assessment systems, analytics dashboards, and AI services. Explicit decision rules (Deber & Goel, 1990) govern mastery progression, risk escalation, integrity review, and AI uncertainty handling. Data minimization, role-based access, audit logs, and fairness monitoring are enforced throughout. Figure 4 shows operational workflows of SMART-OU for Integrity-aware remote education.

Figure 4: SMART-OU Framework for AI Remote Teaching



Methodology and Model Development

This paper develops SMART-OU using a design-oriented approach (Wright, 2017) that combines theory-driven synthesis with practical requirements from Open University operations. The model is intended to be implementable with common learning management systems and support structures, while keeping academic decisions under human authority. Following steps are followed.

Step 1

Problem and context analysis. Remote teaching challenges in open universities were mapped into operational constraints, including large cohort scale, asynchronous study patterns, diverse learner readiness, and limited instructor time.

Step 2

Design requirements. Requirements were derived to ensure that AI supports, rather than replaces, academic judgment. Key requirements include explainability, low bandwidth accessibility, integrity-by-design, and human-in-the-loop escalation for high-stakes decisions.

Step 3

Framework construction. The model components and workflows were assembled into a staged learner journey and instructor workflow, then aligned with data flows, decision rules, and governance controls.

Step 4

Validation plan. A pilot evaluation plan with measurable outcomes and ethical safeguards is defined to support iterative refinement and scalability across programs.

Model Reliability and Validity

Instead of using a single empirical experiment, the SMART-OU model's design structure, theoretical foundation, and implementation techniques address its validity and reliability (Tracey, 2009). Since SMART-OU is suggested as an institutional framework for AI-enabled remote instruction in open universities, its reliability is demonstrated by conceptual, operational, and procedural guarantees that enable consistent and significant implementation in a variety of educational settings.

Reliability: The SMART-OU model has a high degree of reliability due to standardized and repeatable workflow that controls interactions between learners and the system between the learners and the instructor. The model establishes clear steps in the learning process (diagnose, scaffold, practice, assess, and support) and instructor practices (design, monitor, intervene and improve), and they do not change based on the course discipline or size of the cohort. These processes are enabled by consistent information sources like learning management system activity logs, assessment records and learner support interactions which allow the consistent interpretation of engagement and performance indicators. Rule based decision support mechanisms also enhance operational reliability. The predefined criteria are used to derive early warning signals, adaptive sequencing triggers and feedback processes as opposed to ad hoc judgments. Notably, the human-in-the-loop approach improves reliability because it enables tutors and instructors to interpret analytics outputs in the context of the pedagogy and contextually to minimize variability due to automated misclassification or sparse data. Consequently, SMART-OU enhances the use of interventions consistently, but the institution and a learner specific context can be flexible.

Validity: The SMART-OU model is proved to be valid in several aspects such as content validity, construct validity, and face validity. The process of ensuring the content validity is facilitated by the correspondence between SMART-OU components and the highly known challenges and best practices reported in the literature concerning open and distance learning, learning analytics, and academic integrity (Amigud at el., 217). All of the elements of the model, like adaptive scaffolding, formative feedback, and early risk detection, and integrity-aware assessment, will supply answers to problems that have been empirically identified, such as delayed feedback, learner disengagement, high dropout rates, and academic misconduct in remote education settings. The explicit mapping of educational objectives and the functions of AI in the framework reinforces construct validity. As an illustration, the concept of learner engagement is measured using observable features like participation patterns and mastery progressions; learner retention is facilitated with the help of analytics-driven early intervention and learner support processes; and academic integrity is met by authentic assessment design and supervised AI-assisted similarity and anomaly detection. These mappings are necessary to make sure that the model is actually measuring and supporting the constructs it claims to affect, not using proxy or purely behavioral measures. The face validity is determined by the feasibility of the SMART-OU model in the current institutional structures. The framework is structured in a way that its processes can be identifiable and interpreted by the instructors, administrators and learners as it is intended to be run on the basis of the commonly available learning management systems, assessment systems and student support services. These aspects of governance, transparency, and academic oversight also add to the belief of the stakeholders in the suitability of the model to large-scale Open University environments.

Implementation-Oriented Validation: Although the current work is dedicated to the conceptual and operational design of SMART-OU, the model assumes a distinct route of empirical validation with the help of the gradual implementation. An evaluation of measurable results in the form of pilot deployments to chosen courses or programs can be conducted, i.e., learner retention, engagement consistency, feedback turnaround time, instructor workload, and frequency of academic integrity escalations (Algewatta & Manathunga, 2025). These assessments are supposed to be held within the recognized ethical and governance standards, which would guarantee the minimization of data, fairness, and human judgment. A combination of theoretical bases, standardized structure, and validation strategy that can be applied in practice makes SMART-OU reliable enough to be used as a powerful framework in remote teaching based on AI in open universities.

System Architecture and Data Flow

SMART-OU can be implemented as a layered architecture (Gasser & Almeida, 2017) that connects the learning management system, assessment tools, and student support services through controlled data pipelines.

- *Layer 1:* Data sources. Typical sources include LMS activity logs, assessment submissions and grades, discussion participation, and support interactions (helpdesk and tutoring records).
- *Layer 2:* Data processing and feature store. Event data is cleaned and aggregated into interpretable features such as time since last login, missed deadlines, prerequisite quiz mastery, and unresolved support requests.
- *Layer 3:* Decision support services. This layer hosts adaptive sequencing rules, formative feedback services, early warning risk scoring, and instructor dashboards. It also reports uncertainty and confidence to avoid over-trust in automation.
- *Layer 4:* Human action and governance. Tutors, instructors, and advisors review outputs, take actions, and record outcomes. Governance controls include role-based access, audit logs, and periodic fairness review. Table 3 shows example data sources and decision support use in SMART-OU.

Table 3: SMART-OU Data Sources and Uses

Data source	Example features	Typical use
LMS activity logs	Time since last login, micro-unit completion, content revisits	Engagement monitoring, nudges, adaptive pacing
Assessment records	Missing submissions, quiz mastery, rubric dimension scores	Mastery progression, targeted practice, feedback triggers
Discussion and messages	Question frequency, unresolved threads, participation patterns	FAQ improvement, facilitation support, social presence
Support services	Ticket volume, resolution time, repeat issues	Workload balancing, escalation to advising, accessibility support

Risk Prediction and Intervention Prioritization

Risk prediction and intervention prioritization Early warning alerts are stratified through various data points. These alerts, while not meant to be automated, help tutors to prioritize outreach, and automate interventions with a focused purpose.

Implementation Roadmap for Open Universities

SMART-OU can be adopted in staged steps to reduce disruption and manage risk.

- *Phase 1:* Foundation. Standardize course templates, outcomes, rubrics, and LMS event logging. Define the AI governance charter, roles, approvals, and audit responsibilities.
- *Phase 2:* Low-stakes AI. Deploy AI assisted content checks (readability, accessibility), FAQ assistants restricted to course content, and rubric aligned formative feedback for practice tasks.
- *Phase 3:* Analytics and interventions. Introduce dashboards for mastery and engagement,

implement early warning rules, and run human coordinated outreach for at-risk learners.
- *Phase 4:* Integrity-aware assessment. Expand authentic assessments, use similarity and anomaly checks with documented human review, and refine assessment design based on evidence.
- *Phase 5:* Continuous improvement. Run course-level experiments, compare cohorts ethically, and revise decision rules, content scaffolds, and support pathways each delivery cycle.

Limitations and Risk Management

SMART-OU is a conceptual and operational model, so its effectiveness depends on implementation quality and the maturity of local LMS, data practices, and support services. Risk scoring and adaptive sequencing can be less accurate when learner activity data is sparse, for example due to intermittent connectivity or offline study routines. For this reason, SMART-OU treats analytics outputs as decision support signals, not as automated labels.

A second limitation is that AI assisted feedback can drift from institutional standards if the underlying content base, rubrics, and examples are not continuously maintained. SMART-OU therefore requires governance controls such as versioned rubrics, approved knowledge bases for assistants, and routine audit sampling of AI feedback quality. Finally, privacy and fairness risks remain if student data is over collected or if models behave differently across groups. Data minimization, clear consent, and periodic fairness monitoring are essential to reduce these risks.

Conclusion

This study presented SMART-OU as an integrated and pedagogy- driven framework for AI-enabled remote teaching that directly addresses long-standing challenges in open universities, including limited personalization, delayed feedback, learner disengagement, and academic integrity risks. This approach to prediction and intervention prioritization provides a data driven approach to prediction and intervention prioritization, crossing the boundary from the tool focus to the more holistic approach of the institution as an integrating artificial intelligence into learning design, and learner support and data driven feedback and assessment. human-in-the-loop preserves academic integrity and fairness while addressing potential ethical concerns prediction and prioritization.

The approach primarily focused on learning and feedback provides a sound pedagogical practice to use artificial intelligence prediction systems for achieving an educational goal, rather than a simple efficiency gain. The model's potential to provide a cohesive and transparent pathway to the use of artificial intelligence in large scale distance education learning systems is apparent, particularly within the scope of the distance education learning systems. CENTRAL to the models potential is the ethos within the design to provide tangible support to educators within distance education. The holistic approach distinguishes the platform from more traditional designs and predicts an institution's ability to adapt systems in a complex environment with more traditional educational systems. The framework supports distance education systems and models and provides a pathway to integrating ethical systems to artificial intelligence within distance education as a tertiary focus.

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