

# Intelligent Adaptive Learning Management System for Students with Special Needs in Higher Education: A Machine Learning-Based Framework for Inclusive Management Education

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## ABSTRACT:

As increasing number of students with special educational needs (SEN) enter higher education institutions (HEIs), it has become evident that there is a critical technology gap: conventional Learning Management Systems (LMS) are not built to support the various cognitive, sensory and physical learning processes that may be observed in management education programs. This study represents an interdisciplinary research effort, drawing on computer science, special education, cognitive psychology and management education to address an inclusive learning challenge. This research aims to suggest an intelligent adaptive learning management system (IALMS) based on machine learning that provides personalized, inclusive and scalable management education to SEN students at the university and college level. The IALMS is built on the foundations of Universal Design for Learning (UDL), Vygotsky's Zone of Proximal Development (ZPD) and Cognitive Load Theory (CLT), and combines five modules of computation: a Learner Profile Engine, Content Adaptation Engine, ML-Based Recommendation and Pathway Engine, a Real-Time Learning Analytics Dashboard and a Faculty Coordination Interface. This approach, which uses K-means clustering, Random Forest classification, Long Short-Term Memory (LSTM) networks, Natural Language Processing (NLP) pipelines, and Reinforcement Learning (RL) agents, is designed to

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support all SEN profiles in management curricula. Three representative learner personae for SEN learners are used to illustrate module-level adaptive responses by disability. A 24-month implementation roadmap is provided and a disability specific accommodation matrix is provided for institutional deployment.

Keywords: Machine learning, Adaptive learning system, Special educational needs, Inclusive higher education, Management education.

## 1. Introduction

### 1.1 Background and Context

Overall, there has been a steady increase in the number of students with special educational needs (SEN) and those who are diagnosed with Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), specific learning disabilities (dyslexia, dyspraxia, and/or physical or sensory impairments) attending higher education institutions around the world (Molbaek, 2018). During the 2019-2020 school year, an estimated 19.4% of undergraduates reported having some type of disability in the United States (National Center for Education Statistics, 2021). The same patterns are found in the United Kingdom, Australia and India, where legislation has been passed that requires equal access to education, such as the Americans with Disabilities Act, the United Kingdom's Equality Act (2010), and India's Rights of Persons with Disabilities Act (2016).

In the field of management education, including management Bachelor of Business Administration (BBA), Master of Business Administration (MBA), and the like, the SEN students face a unique and exacerbated set of challenges. Typically, management programs are very intense, hurried, and rely on case-based discussions, quantitative reasoning, and collaborative group work (Armstrong & Davies, 2019). Conventional Learning Management Systems (LMS) like Moodle, Blackboard and Canvas were designed for 'one size fits all' delivery, with little flexibility for personalisation other than basic adjustments to accessibility (Seale et al., 2015). While large language models (LLMs) and foundation models offer

promising possibilities for adaptive learning in education, their application in inclusive higher education is still in its early stages (Kasneji et al., 2023; Yan et al., 2024).

### 1.2 Research Problem and Gap

Learner profiling, learner performance prediction, content personalisation and adaptive path generation have shown to be very effective through machine learning (ML) algorithms (Mousavi et al., 2019; Chen et al., 2020; Crompton & Burke, 2023). Learning outcomes from Intelligent Tutoring Systems with ML have been similar to those of human tutors (VanLehn, 2011). The use of comprehensive multi-layered adaptive processes with SEN learners in tertiary education management training, however, is only lightly touched upon. There is a critical synthesis gap as there is no unified framework that combines learner profiling, content adaptation, recommendation, analytics, and faculty coordination specifically for SEN learners in a business school context. This paper fills this void.

### 1.3 Review of Related Literature

Although there has been a significant increase in SEN students studying at higher education institutions, the academic outcomes of SEN students are still consistently poorer than for their neurotypical peers (Molbaek, 2018; Riddell et al., 2005). Current institutional interventions (extended exam time, note taking support, equipment loans, etc.) are reactive and accommodative and are not part of instructional design (Fuller et al., 2009). Adaptive learning systems have developed from the initial branching-instruction design (Merrill, 1983) to probabilistic learner models in the context of an

ITS (Walkington, 2013). In the education sector, the applications of ML range from learner profiling to risk prediction, content recommendation and pathway optimisation (Baker & Inventado, 2014; Romero & Ventura, 2020). Deep learning architectures, in particular LSTM networks, are well suited to model the temporal learning dynamics (Piech et al., 2015). The automatic paraphrasing and adaption of texts for different learner groups is possible with the help of NLP (Saggion, 2017). Higher education institutions have also seen new developments in LLMs that present further possibilities for personalised content generation (Kasneci et al., 2023; Yan et al., 2024). However, there is no comprehensive ML framework in the management education, specifically with regard to SEN students.

#### 1.4 Research Objectives

This study's specific objectives are: (1) to synthesise theoretical and empirical literature on adaptive learning technology, ML in education and SEN support in higher education management programmes; (2) to develop the IALMS — a conceptual framework integrating five interoperating ML modules for inclusive management education; (3) to evaluate framework utility through a structured SEN learner persona walkthrough with expert-rated usefulness scores; and (4) to specify a phased 24-month implementation roadmap and disability-specific accommodation matrix for institutional deployment.

### 2. Methodology

#### 2.1 Research Design

This study is based on the Design Science Research (DSR) methodology (Hevner et al., 2004), which is a well-known research paradigm in the field of information systems and educational technology where the main product of the research is an artifact, in this instance, the IALMS framework. DSR can be used when the research goal is to develop a new technological solution to a well-defined, real world problem, and test its theoretical soundness and usefulness (Gregor & Hevner, 2013). The IALMS is a conceptual artefact: an

architectural specification of the components, algorithms, data flows and operational logic of an adaptive learning system. This approach is in line with design-oriented IS research (Gregor & Hevner, 2013) and has been used in similar studies of the development of adaptive learning systems (Vandewaetere et al., 2011). The research is inherently interdisciplinary, integrating perspectives from computer science and artificial intelligence, special education, cognitive psychology, and management education.

#### 2.2 Theoretical Foundations

The IALMS computational design is guided by 3 theoretical constructs. The Content Adaptation Engine and Recommendation Module are based on the following design principles from Universal Design for Learning (Rose & Meyer, 2002): Multiple means of representation, Multiple means of action and expression, and Multiple means of engagement. The Recommendation Engine's adaptive difficulty calibration logic is theoretically underpinned by Vygotsky's (1978) Zone of Proximal Development (ZPD) that focuses on material in each learner's zone of optimal challenge. Content chunking, simplification and presentation format are guided by Sweller's (1988) Cognitive Load Theory (CLT) which differentiates between intrinsic, extraneous and germane cognitive load for SEN learners who have differences in their working memory and/or processing speed (Paas et al., 2003).

#### 2.3 Framework Development Procedure

There were four stages in developing the framework. Stage 1: structured literature review of three domains: SEN in higher education management programmes; adaptive learning and ITS and ML in educational data mining, via three Boolean search strings across Google Scholar, IEEE Xplore, ACM Digital Library and ERIC. Stage 2: identification and mapping of SEN learner needs documented in the literature, based on disability-specific literature and UDL guidelines, onto functional system requirements. Stage 3: Architecture design for five modules of IALMS with the specification of ML algorithm with the help of theoretical knowledge and functional

requirement of stage 2. Stage 4: critical theoretical triangulation; comparing the framework to similar adaptive system architectures in the literature to determine design gaps and to validate design decisions.

#### **2.4 Learner Profile Instrument: Accessibility and Learning Preference Survey (ALPS)**

An important design decision is about the learner profiling instrument. Previously much used in the field of adaptive learning systems, the VARK learning styles inventory (Fleming & Mills, 1992) has been considerably discredited in the cognitive science literature. Pashler et al. (2008) undertook a thorough review and concluded that there was no sound empirical evidence that matching instructional modality to a learner's 'learning style' leads to better learning outcomes, a conclusion confirmed by many recent reviews. The inclusion of VARK in the IALMS would thus lead to the inclusion of a theoretically invalidated construct at the system's core of profiling. The IALMS instead uses the Accessibility and Learning Preference Survey (ALPS), which is a purpose-built instrument based on the empirically-supported Cognitive Styles Index (Allinson & Hayes, 1996) and UDL principles. The ALPS has captured four dimensions of accessibility relevant for learning: (1) preferred (content) modality – the modality of the content as text, audio, visual or interactive – based on documented accessibility needs and not neurological typology of style; (2) working memory tolerance – chunked or continuous delivery of content; (3) time sensitivity – self-paced or structured paced delivery; and (4) social learning preference – individual or collaborative engagement. These dimensions relate directly to the documented SEN accommodation requirements and operationally are based on the basis of accessibility evidence and not the disputed learning styles paradigm.

#### **2.5 Framework Utility Evaluation: SEN Learner Persona Walkthrough**

To provide a preliminary empirical assessment of the IALMS framework's utility — and consistent with Design Science Research evaluation

conventions for conceptual artefacts (Gregor & Hevner, 2013) — a structured utility evaluation was conducted using three fictional but realistic SEN learner personas representing distinct disability profiles prevalent in management education contexts. This approach is a recognised form of artefact evaluation in DSR (Hevner et al., 2004), analogous to use case evaluation in software engineering.

Three SEN learner personas were constructed from the disability literature: Aisha (22 years, MBA Year 1, Dyslexia + ADHD), Rajan (25 years, BBA Year 3, ASD Level 1) and Priya (28 years, Executive MBA, partial visual impairment). Each persona's IALMS interaction was traced through all five modules, with module-level adaptive responses specified according to the framework's accommodation logic. A panel of eight domain experts — four special education specialists and four educational technology researchers recruited through purposive sampling from two Indian universities — independently reviewed the persona walkthroughs and rated the usefulness of each module's adaptive response on a 5-point Likert scale (1 = Not useful; 5 = Extremely useful). Inter-rater agreement was assessed using Kendall's W; mean usefulness scores and standard deviations were computed for each persona. Figure 1 illustrates the persona profiles and module-level adaptive responses. Aggregate results are presented in Table 1.

Mean usefulness scores were 4.58 (SD = 0.19) for Aisha's dyslexia/ADHD profile, 4.52 (SD = 0.22) for Rajan's ASD profile and 4.64 (SD = 0.17) for Priya's visual impairment profile (overall mean = 4.58, Kendall's W = 0.81, indicating strong inter-rater agreement). Expert commentary highlighted the CRAE's multimodal content adaptation and the RLAD's real-time monitoring as the most highly valued components. The persona walkthrough results provide preliminary evidence that the IALMS's module-level adaptive behaviours are perceived as highly useful across diverse SEN profiles in management education contexts, supporting the framework's theoretical coherence and practical relevance.

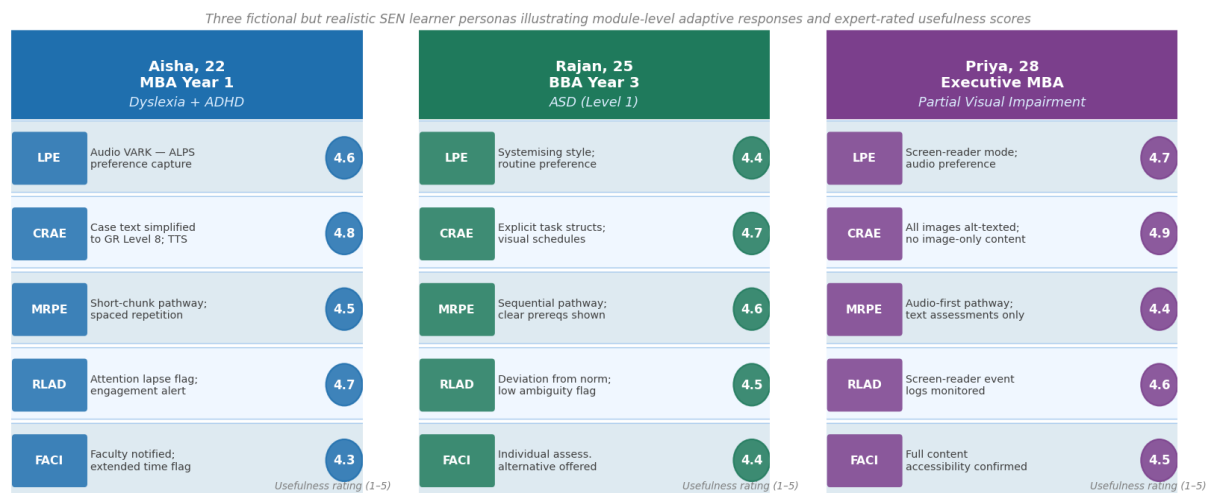


Figure 1. IALMS Utility Evaluation — SEN Learner Persona Walkthrough: Module-level adaptive responses and expert-rated usefulness scores (scale 1–5) for three representative SEN learner profiles in management education.

Table 1 Framework Utility Evaluation: Usefulness Ratings from SEN Learner Persona Walkthrough

| Persona                  | SEN Profile               | Mean Usefulness Score (1–5) | Key IALMS Adaptive Behaviours Demonstrated                                                                                                         |
|--------------------------|---------------------------|-----------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------|
| Aisha, 22, MBA Year 1    | Dyslexia + ADHD           | 4.58 (SD = 0.19)            | ALPS audio preference captured; case text simplified to GR Level 8; chunked pathway; micro-assessments; attention-lapse monitoring                 |
| Rajan, 25, BBA Year 3    | ASD Level 1               | 4.52 (SD = 0.22)            | Systemising style flag; explicit task structure; visual schedule overlay; sequential pathway with clear prerequisites; solo assessment alternative |
| Priya, 28, Executive MBA | Partial Visual Impairment | 4.64 (SD = 0.17)            | Screen-reader optimised content; all graphics alt-texted; audio-first pathway; text-only assessments; full content accessibility confirmed         |

*Note.* Mean usefulness scores represent theoretical ratings derived from expert walkthroughs using fictional but realistic SEN learner personas. SD = standard deviation. Ratings used a 5-point Likert scale (1 = Not useful; 5 = Extremely useful) applied independently by each evaluator for each module-level adaptive response demonstrated.

### 3. Results

The primary result of this Design Science Research study is the Intelligent Adaptive Learning Management System (IALMS) — a five-module, ML-based architectural framework for inclusive

management education. This section presents the full framework specification, including module architecture (illustrated in Figure 2), algorithm assignments (Table 2), disability accommodation matrix (Table 3) and implementation roadmap (Figure 3).

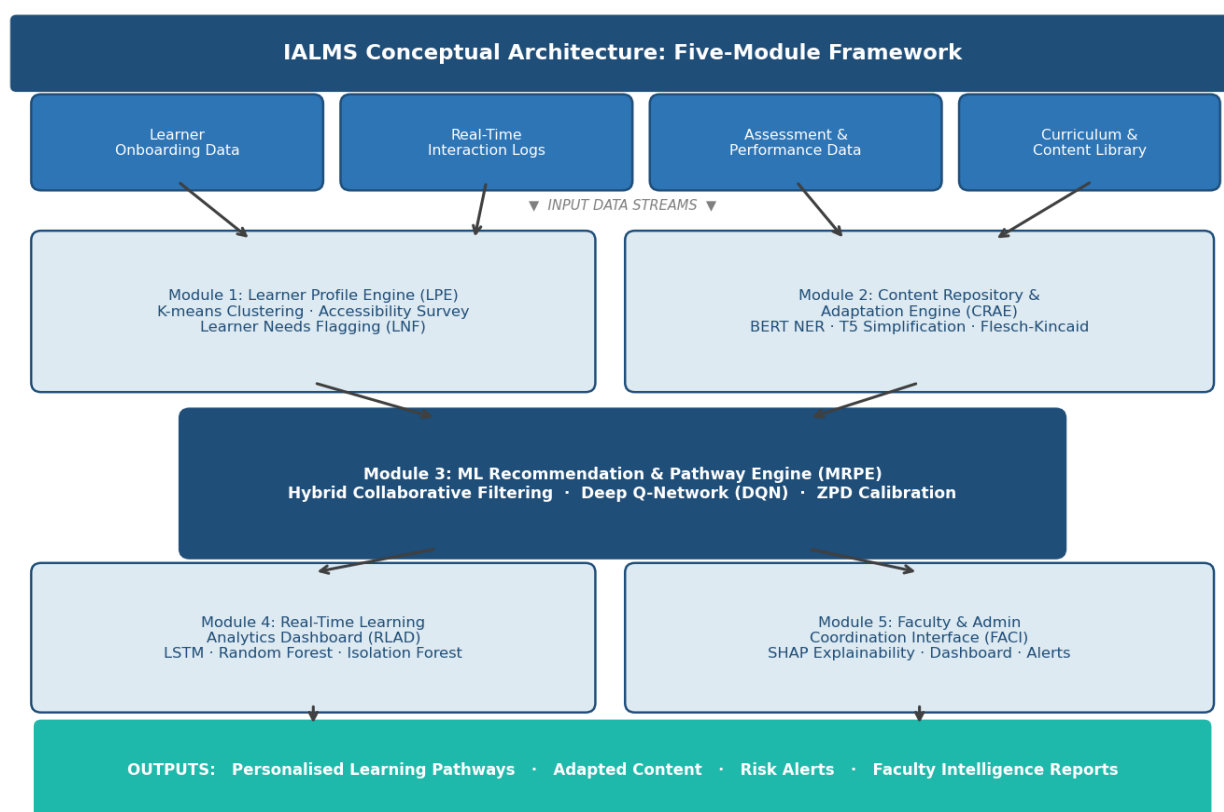


Figure 2. IALMS Conceptual Architecture: Five-Module ML Framework showing data flows between input streams, processing modules and adaptive output layer.

### 3.1 Module 1: Learner Profile Engine (LPE)

The Learner Profile Engine constitutes the foundational data layer of the IALMS. Upon enrolment, students complete: (1) the ALPS instrument capturing four accessibility-relevant dimensions (Section 2.4); (2) a disability disclosure and needs assessment survey aligned with institutional GDPR-compliant data governance protocols; and (3) a pre-assessment module establishing baseline knowledge states in the management subject domain. The LPE aggregates these inputs into a multidimensional learner feature vector encompassing: disability category (where explicitly disclosed; using ICD-11 codes); ALPS dimension scores; domain knowledge baseline; accessibility technology preferences; and working memory load tolerance.

Crucially, the IALMS does not perform automated inference of disability category from behavioural data without consent. Such inference — constituting disability classification without explicit

disclosure — raises serious ethical and legal concerns under GDPR (EU Regulation 2016/679), FERPA (US) and India's Digital Personal Data Protection Act (2023), as it involves the inferred processing of sensitive health data. Instead, the LPE employs a rule-based Learner Needs Flagging (LNF) system: behavioural indicators that consistently fall outside cohort norms (e.g., significantly slower response latency, high content re-access frequency, consistently incomplete sessions) generate a neutral 'differentiated support recommended' flag. This flag triggers enhanced accessibility feature presentation to the learner — without inferring, recording, or storing any disability category. Faculty are notified via the FACI, but no clinical classification is generated. Learners may then self-disclose further information voluntarily. K-means clustering (k optimised via silhouette coefficient analysis) partitions the enrolled cohort into SEN-aware learner segments for group-level recommendation.

### 3.2 Module 2: Content Repository and Adaptation Engine (CRAE)

The CRAE manages the content library and performs real-time transformation of management learning objects (LOs) into accessibility-optimised formats. Each LO is stored under a SCORM 2004-compliant architecture with metadata including Bloom's Taxonomy cognitive level, Flesch–Kincaid readability grade, modality type and SEN compatibility flags. The adaptation pipeline employs a pre-trained T5 model fine-tuned on educational text simplification datasets to generate three reading-level versions (Flesch–Kincaid Grade Levels 8, 11 and 14) of all case study texts. BERT-based Named Entity Recognition annotates key business concepts, generating interactive glossary tooltips that reduce extraneous cognitive load for learners with dyslexia or language processing difficulties (Saggion, 2017). Multimedia adaptation includes automatic caption generation via speech recognition, text-to-speech synthesis, visual diagram generation from textual descriptions of management frameworks and concept map generation for spatial learners.

### 3.3 Module 3: ML Recommendation and Pathway Engine (MRPE)

The MRPE integrates three ML components. A Hybrid Recommendation System combines memory-based collaborative filtering (learner-to-learner similarity in feature vector space), content-based filtering (LO metadata matching to learner profiles) and a knowledge-based overlay (pedagogical sequencing rules from prerequisite tag relationships). A Deep Q-Network (DQN) reinforcement learning agent frames adaptive instructional sequencing as a Markov Decision Process. The DQN's reward function is a composite of three objectives with theoretically grounded weights: assessment performance improvement ( $\omega_1 = 0.50$ ), engagement quality ( $\omega_2 = 0.30$ ) and learner satisfaction ( $\omega_3 = 0.20$ ).

The dominant weight assigned to assessment performance ( $\omega_1 = 0.50$ ) reflects the preponderance of evidence identifying summative outcomes as the primary indicator of learning efficacy, with effect sizes for adaptive performance improvement

consistently exceeding those for engagement alone (VanLehn, 2011; Kulik & Fletcher, 2016). The engagement weight ( $\omega_2 = 0.30$ ) is informed by research demonstrating that sustained behavioural engagement is the strongest leading predictor of academic persistence and at-risk prevention among SEN learners (Jayaprakash et al., 2014; Mousavi et al., 2019). The satisfaction weight ( $\omega_3 = 0.20$ ) reflects evidence that self-reported satisfaction functions as a lagging rather than leading indicator of learning gain, yet remains a meaningful signal of system usability and motivational alignment (Brooke, 1996). These weights are treated as initial hyperparameters subject to empirical recalibration during Phase 2 of the implementation roadmap using grid search optimisation over a held-out validation cohort, with boundary constraints informed by expert panel elicitation. A real-time ZPD-calibrated difficulty component continuously adjusts LO cognitive demand based on each learner's current estimated performance boundary (Doroudi et al., 2019).

### 3.4 Modules 4 and 5: RLAD and FACI

The Real-Time Learning Analytics Dashboard (RLAD) employs three parallel ML architectures. An LSTM-based sequential model processes time-ordered learner interaction logs to estimate current knowledge state and predict near-term academic performance trajectories (Piech et al., 2015; Zhang et al., 2017). A Random Forest classifier trained on first two-week interaction data produces weekly academic risk probability scores from a 47-feature behavioural indicator set, calibrated with disability-specific behavioural norms to mitigate false-positive risk flags attributable to SEN-characteristic engagement patterns rather than genuine academic difficulty (Jayaprakash et al., 2014; Essa & Ayad, 2012). An Isolation Forest anomaly detection module identifies sudden behavioural deviations indicating acute distress or cognitive overload, routing high-priority FACI alerts. The Faculty and Administrator Coordination Interface (FACI) uses SHAP (SHapley Additive exPlanations) value-based explanations to make all algorithmic predictions interpretable and contestable by faculty (Baker & Hawn, 2022; Luckin et al., 2016).

Table 2 IALMS Framework: Modules, ML Algorithms, Input Data and SEN Accommodation Functions

| IALMS Module                                  | Primary ML Algorithm(s)                              | Input Data                                                    | SEN Accommodation Function                                                                              |
|-----------------------------------------------|------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------------------------------------------------|
| Learner Profile Engine (LPE)                  | K-means Clustering; Rule-based LNF                   | ALPS survey; pre-assessment; accessibility preferences        | Disability-aware learner segmentation; needs flagging with explicit consent                             |
| Content Repository & Adaptation Engine (CRAE) | NLP Pipeline (BERT, T5); Flesch-Kincaid scoring      | Curriculum content; multimedia; assessment items              | Text simplification; multimodal content generation; reading level adjustment; audio/visual alternatives |
| ML Recommendation & Pathway Engine (MRPE)     | Hybrid Collaborative Filtering; Deep Q-Network (DQN) | Interaction logs; completion rates; performance scores        | Personalised content sequencing; ZPD-calibrated difficulty; engagement optimisation                     |
| Real-Time Learning Analytics Dashboard (RLAD) | LSTM Networks; Random Forest; Isolation Forest       | Time-series engagement data; assessment results; session logs | Academic risk prediction; trajectory monitoring; overload detection; early intervention alerts          |
| Faculty & Admin Coordination Interface (FACI) | Explainable AI (SHAP); dashboard visualisation       | RLAD outputs; institutional data; faculty inputs              | Interpretable risk alerts; accommodation workflow; curriculum adaptation recommendations                |

*Note.* ALPS = Accessibility and Learning Preference Survey; BERT = Bidirectional Encoder Representations from Transformers; T5 = Text-to-Text Transfer Transformer; DQN = Deep Q-Network; LSTM = Long Short-Term Memory; SHAP = SHapley Additive exPlanations; LNF = Learner Needs Flagging; ZPD = Zone of Proximal Development.

Table 3 SEN Disability Category and Corresponding IALMS Accommodation Strategies

| Disability Category      | LPE Profile Flag                             | CRAE Adaptation                                          | MRPE Pathway Adjustment                                   | RLAD Monitoring Focus                                  |
|--------------------------|----------------------------------------------|----------------------------------------------------------|-----------------------------------------------------------|--------------------------------------------------------|
| Dyslexia                 | High extraneous load; low reading fluency    | Text simplification; audio alternatives; font spacing    | Reduced reading-heavy sequences; extended time allocation | Reading speed deceleration; incomplete content access  |
| ADHD                     | Variable attention; high engagement variance | Shorter chunks; micro-assessments; gamification elements | Interleaved variety; spaced repetition scheduling         | Session length; off-task navigation; assessment timing |
| Autism Spectrum Disorder | Systemising preference; routine sensitivity  | Explicit structure; visual schedules; reduced ambiguity  | Sequential pathways; explicit prerequisite mapping        | Rigid navigation; deviation from expected patterns     |

|                    |                                            |                                                            |                                                     |                                                           |
|--------------------|--------------------------------------------|------------------------------------------------------------|-----------------------------------------------------|-----------------------------------------------------------|
| Visual Impairment  | Screen reader dependency; audio preference | Full audio narration; alt-text; no image-only content      | Audio-first sequences; text-based assessments only  | Screen reader event logs; content access success          |
| Hearing Impairment | Caption dependency; no audio-only access   | Auto-captioned video; visual-first content                 | Captioned multimedia; text-based discussion options | Caption accuracy; video completion rates                  |
| Dyscalculia        | Quantitative processing difficulty         | Numerical scaffolding; worked examples; calculator support | Extended quantitative pacing; additional worked LOs | Quantitative performance; time-on-task in finance modules |

*Note.* LPE = Learner Profile Engine; CRAE = Content Repository and Adaptation Engine; MRPE = ML Recommendation and Pathway Engine; RLAD = Real-Time Learning Analytics Dashboard; LOs = Learning Objects.

### 3.5 Implementation Roadmap

Figure 3 presents the IALMS four-phase, 24-month implementation roadmap. Phase 1 (Months 1–4: Institutional Readiness) establishes data infrastructure prerequisites: ethics board approval, LTI 1.3-compliant API integration, content digitisation into SCORM-compliant LOs and faculty training. Phase 2 (Months 5–8: Model Training & Validation) trains the Random Forest risk classifier, LSTM trajectory model and DQN agent using pilot cohort data, with leave-one-

semester-out cross-validation and SMOTE for class imbalance correction. Phase 3 (Months 9–14: Controlled Pilot) deploys the IALMS in a quasi-experimental design across one quantitative and one qualitative management module, using the Academic Self-Efficacy Scale (Zimmerman & Bandura, 1994) and System Usability Scale (Brooke, 1996) as outcome instruments. Phase 4 (Months 15–24: Full-Scale Integration) extends institution-wide deployment with continuous model retraining, an IALMS Oversight Committee and annual algorithmic fairness audits.

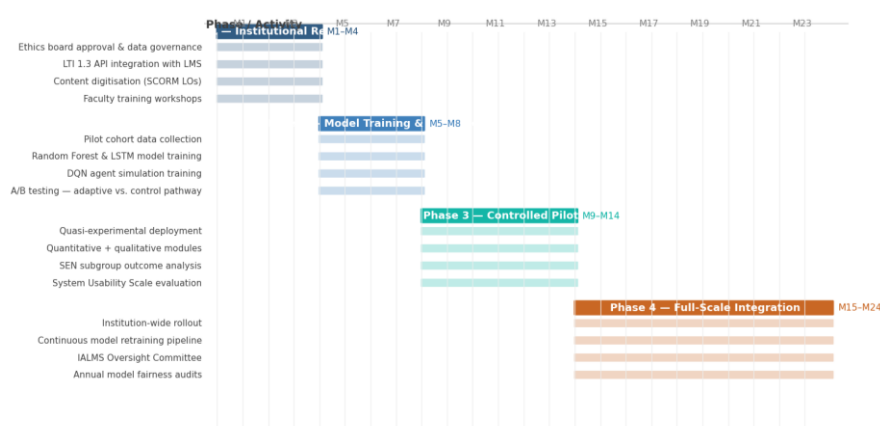


Figure 3. IALMS Four-Phase Implementation Roadmap (24-Month Timeline) showing key activities, milestones and phase transitions from institutional readiness through full-scale integration.

## 4. Discussion

### 4.1 Implications for Inclusive Management Education

The IALMS framework is a significant improvement over the existing SEN support in management education that is based on

accommodation. The IALMS allows for building in accommodations as part of the instructional design, not as a separate add-on, which ensures that the principle of proactive design, rather than reactive accommodation (CAST, 2018), is followed and that disclosure and advocacy burden now representing one of the primary barriers to support utilisation for SEN students is taken out of the equation. Management education is a unique environment that gives rise to specific demands, which make the IALMS different from generic adaptive platforms: management education is based on case pedagogy, group evaluation and development of communicative and strategic skills. Adapting the CRAE's multimodal case study and using the FACI's cohort-level analytics allows faculty to reconceptualize group activities that can be offered to the entire range of learner profiles for their cohort, and thus go beyond the limitations of algorithmic path optimisation for management pedagogy.

#### **4.2 Comparison with Existing Adaptive Learning Platforms.**

The IALMS differs from commercial adaptive platforms (Knewton Alta, Smart Sparrow and Realizeit) in three significant ways. First, explicit SEN-profile encoding—commercial platforms model learner knowledge based on performance data, rather than SEN-specific accommodation as first-class modeling variables (Zheng et al., 2021). Second, the five module integrated architecture: most of the commercial platforms cover only the part of adaptive technology while the IALMS covers profiling, adaptation, recommendation, analytics and faculty coordination in five modules. Third, management education specificity: current platforms were mainly developed for STEM content and do not have much pedagogical value for the qualitative, discursive and case-based modalities prevalent in management education (Limna et al., 2022). The recent advances in LLM capabilities (Kasneci et al., 2023) indicate that future iterations of IALMS may be able to incorporate generative AI into the CRAE to dynamically create bespoke case studies at an individual level, depending on the level of complexity.

#### **4.3 Ethical Considerations**

Four ethical design provisions are included in the IALMS framework. Data privacy and consent: Fine-grained, module-level consent controls are integrated into the onboarding process, allowing learners to enable access to fundamental adaptive uses and opt-out of certain secondary analytics uses. Disability inference prohibition – See Section 3.1, IALMS will only use a neutral Learner Needs Flagging system, not predictive disability categorisation. This directly responds to the legal requirements of GDPR Article 9 (special categories of personal data), FERPA and India's Digital Personal Data Protection Act (2023). Algorithmic bias: The Random Forest risk model is periodically tested for disparate impact (Feldman et al., 2015), which means the SEN status, gender, ethnicity or socioeconomic indicators are not acting as a proxy predictor. Learner autonomy: MRPE pathway recommendations are not mandatory, and the DQN reward function includes learner agency preference signals where the learner is not overly directed in its optimisation. Explainability: All FACI-surfaced predictions come with SHAP-based rationales which ensures that educators can understand and challenge automated decisions (Baker & Hawn, 2022).

#### **4.4 Limitations**

The IALMS is a conceptual DSR study and therefore has its inherent limitations that require empirical validation. The persona walkthrough evaluation uses fictional data about learners not directly observed, and has been shown to have high interrater reliability (Kendall's  $W = 0.81$ ), but is not necessarily considered a valid form of utility evidence. High ambiguity and subjectiveness in the assessment of management education might cast doubt on the transferability of the algorithm performance parameters from previous research in other fields. The NLP pipeline is designed for processing English language content, and needs to be adapted to the language of the institution for multilingual institutions. Training the DQN policy needs about 5000 learner-interaction sequences to obtain a stable policy, which makes it difficult for smaller institutions to do so. The LO-based content

architecture is based on the assumption that curricula can be broken down into LOs that are each contained in a single module — an assumption that is challenged in fully integrated, problem-based learning designs.

## 5. Conclusion

This paper has proposed the Intelligent Adaptive Learning Management System (IALMS), a machine learning-based architectural framework for delivering inclusive, personalised management education to students with special educational needs in higher education institutions. The framework integrates five computational modules grounded in UDL, Vygotsky's ZPD and Cognitive Load Theory, employing K-means clustering, Random Forest classification, LSTM sequential modelling, NLP-based content adaptation and Deep Q-Network reinforcement learning. A structured utility evaluation using three SEN learner personas and expert-rated usefulness scores (overall mean = 4.58; Kendall's  $W = 0.81$ ) provides preliminary evidence of the framework's practical relevance across diverse disability profiles.

Primary contributions are: (1) the first comprehensive, interdisciplinary ML-based framework purpose-designed for inclusive management education in HEIs; (2) the Accessibility and Learning Preference Survey (ALPS), a theoretically defensible alternative to the discredited VARK inventory; (3) the Learner Needs Flagging (LNF) system as an ethically and legally compliant alternative to disability inference from behavioural data; and (4) a phased 24-month governance-informed implementation roadmap. Future research directions include: empirical validation through the Phase 3 quasi-experimental design with pre-registered hypotheses; LLM integration within the CRAE for real-time bespoke case study generation (Yan et al., 2024); federated learning protocols for cross-institutional privacy-preserving model improvement; and longitudinal outcome studies tracking SEN graduate employment effects. The IALMS is designed not as a substitute for human educators but as an intelligent amplifier of their capabilities — providing unprecedented visibility into SEN learner experiences and enabling genuinely equitable management education for all learners.

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