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FROM EXCLUSION TO EMPOWERMENT: REDESIGNING E-LEARNING TO MITIGATE RISKS FOR DISABLED STUDENTS

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ABSTRACT
The purpose of this study is to develop an AI-based, inclusive e-learning model to reduce the educational risks faced by disabled students. By exploring the potential of AI to support equitable participation in digital learning, this research addresses remaining challenges, including insufficiently adaptable content, social isolation, and varying degrees of access. Using a qualitative multi-case approach, data are drawn from a literature review, interviews, and feedback obtained during focus group discussions with students who have visual, hearing, physical, and cognitive disabilities at three Malaysian universities. Thematic analysis in NVivo found that AI-supported technologies, such as automated captioning, text-to-speech, and predictive learning analytics, support listening comprehension, collaboration, and engagement; however, challenges remain regarding algorithmic bias, privacy, and infrastructure readiness. This led to the development of the AI-Driven Inclusive E-Learning Risk-Mitigation Framework (AI-IERMF), which embraces Universal Design for Learning (UDL) principles for real-time adaptive analytics. Theoretically, this study advances the social model of disability by adopting a predictive risk approach. Practically, it helps policymakers, educators, and developers create transparent, ethically sensitive, and resource-aware e-learning systems. Overall, the study informs inclusive education and shifts accessibility from reactive compliance to proactive digital empowerment.
Keywords : *E-Learning, AI in Education, Disabled Students, Inclusion, Risk Mitigation.*

1. Introduction

With the accelerating pace of development in information and education technology, the learning environment worldwide has changed significantly in recent years. What were once supplemental e-learning sites are now the backbone of the school. Although access and inclusion have improved considerably, students with disabilities still encounter obstacles that hinder their academic engagement and success (Alshahrani, 2023; Choi, 2023). The reliance on online education increased significantly during the COVID-19 pandemic, highlighting that the e-learning systems in place are unable to accommodate a range of students, including those with physical, sensory, or cognitive disabilities (Fauzi et al., 2023).

Both internationally and nationally, disabled people are participating in higher education in significant numbers, but with patchy results. In the United States, 21% of undergraduates self-identified as having a disability in the academic year 2019–2020 (National Center for Education Statistics, 2023). Elsewhere, in the United Kingdom, almost one in five full-time undergraduates (19.9%) reported having at least one disability in 2023–2024; however, continuation rates are slightly lower among many disabled groups than among their non-disabled counterparts (Office for Students, 2023, 2025). Despite progress in participation, there are accessibility obstacles in the digital world. The WebAIM Million (2025) report found that 94.8% of the top 1,000 homepages have violations of the Web Content Accessibility Guidelines (WCAG) 2.0, highlighting the potential impact of accessibility failures on learners who rely on online learning platforms. Similar results have been found in academic studies where Massive Open Online Courses (MOOCs) and Learning Management Systems (LMSs) often do not meet the WCAG 2.1 criteria for people with disabilities, such as visual, motor, and cognitive impairments (Iniesto & Rodrigo, 2024; Rodríguez-Ascaso et al., 2024; Lomellini et al., 2025). The systemic problem also persists at the international level, beyond individual platforms. Typically, only half as many disabled adults have higher education compared to non-disabled adults, and these disparities remain an equity issue in which AI-powered e-learners must include (UNESCO, 2022).

Despite the emerging trend of school digitalization, several problems, such as the physical environment, disengaged staff, inadequate monitoring, and inappropriate pedagogical approaches, limit disabled children's access to quality learning opportunities. Current systems are frequently designed with a 'one size fits all' mentality, failing to account for inclusive experiences when meeting diverse cognitive, sensory, and motor needs (Królak & Zając, 2024). Empirical evidence suggests that a large proportion of Learning Management Systems (LMSs) and Massive Open Online Courses (MOOCs) are still not fully accessible, which creates obstacles for disabled students to be fully included in the educational environments when learning online or via these digital platforms, both at schools, universities or during lifelong learning experiences (Iniesto & Rodrigo, 2024; Lomellini et al., 2025). Similarly, academic and organizational agents often lack the appropriate training and resources to build accessible online spaces, thereby perpetuating systemic social disparities (Lowenthal & Lomellini, 2023).

Web content accessibility standards, such as the WCAG (2.1), do address technical conditions of compliance, but they seldom consider pedagogical inclusive design or adaptation mechanisms that respond to individual learners' needs during the learning process (Afonso et al., 2025; Lomellini et al., 2025). As a result, old-school e-learning systems are unable to identify, anticipate, and avoid risks such as cognitive overload, boredom, or technology fatigue for disabled students. This gap highlights the need for an AI-enabled transformation of e-learning, with intelligent personalization, predictive analytics, and real-time accessibility metering that make e-learning environments more inclusive, resilient, and low-risk.

These facts emphasize the necessity of data-driven adaptive solutions to address educational risks encountered by children with disabilities. Today, AI technologies can greatly help address these disparities by personalizing learning experiences, automating accessibility accommodations, and providing predictive analytics to identify learning risks early. Such advances can help educators and institutions create inclusive spaces that mitigate dropout, increase engagement, and maximize equal access to e-learning opportunities for all students, regardless of ability. Additionally, AI technologies like ChatGPT can empower disabled students in online learning by improving access to content, enabling personalized learning, and supporting communication (Neumann, 2023).

Even though there is growing recognition of digital accessibility, the current e-learning systems are still fundamentally designed for neurotypical and non-disabled learners, without adequately addressing the subtleties of disabled students' needs (Rudolph & Tan, 2023). Surface-level accessibility is the primary target in conventional adaptation scenarios, such as captioning and screen readers. However, serious, deeper barriers such as poor content personalization, social exclusion, or uneven participation rates (Baidoo-Anu, 2023; Dyliaeva et al., 2024) remain unaddressed. This represents a gap that should be addressed through broader approaches, including new assistive technologies, to turn those inclusive, low-risk settings for disabled students in education into more realistic settings (Budiarta & Putra, 2023; Pierrès et al., 2024).

To address these challenges, this study proposes a pioneering framework for modifying e-learning platforms that applies AI techniques (including ChatGPT) to the model. Qualitative analysis and the synthesis of literature reviews, case studies, and user feedback are employed to examine how AI-enabled tools can personalise content, boost interaction, and create inclusive environments for low-risk learning. The one-on-one conversational A+ I can provide is honestly unmatched in a classroom for someone who wants to learn without compromising on the details of why answers are as they are (Atlas, 2023; Modak et al., 2022). This study focuses on practical solutions, including real-time content translation, interactive dialogue systems, and personalized learning paths, which, for instance, are indispensable for reducing the risks students with disabilities face due to communication barriers, content difficulties, and imbalances in participation (Goudar & Shilpa, 2023).

However, there are significant gaps in the current literature. Most of the current literature focuses on accessibility-oriented compliance rather than proactive risk mitigation with AI (Aithal & Aithal, 2023a; 2023b). Research on AI in education primarily focuses on improving student learning, but it does not examine how AI can better support students with disabilities (Fernando et al., 2021; Khalil, Slade & Prinsloo, 2023). Also, despite some recognition of generative AI's transformative potential, few studies offer tangible models or implementations for inclusive e-learning design (Dempere et al., 2023; Lomellini et al., 2025). Such a lack of actionable insights prevents educators, developers, and policymakers from realizing AI's full potential to enrich learning experiences for all learners, particularly for students with disabilities (Rauf et al., 2024).

Thus, the specific study objectives are as follows: (1) To assess the effectiveness of AI-driven accessibility features in improving the usability and inclusivity of e-learning platforms for disabled students, (2) To evaluate the role of AI-based risk-mitigation systems in identifying and reducing learning risks among disabled students, (3) To measure user satisfaction and perceived learning engagement resulting from AI-supported collaborative tools and inclusive design elements. To this end, the study specifies these objectives as evidence-based goals, thereby guiding the research framework in this work toward a focused investigation of practical AI-mediated solutions.

2. Literature Review

With the advent of e-learning platforms, the educational landscape is being reorganized worldwide in a flexible, accessible way for a diverse range of learners. E-learning is both an opportunity and a challenge for students with special needs. Technology, though it could fill the gaps in this conventional learning system, may also widen the gap unless approached with inclusivity (Alshahrani, 2023; Baidoo-Anu, 2023). This study reviews recent literature on e-learning for disabled students to critically explore the potential, limitations, and role of AI in managing risks.

2.1 Accessibility Standards and Inclusive Design in E-Learning for Disabled Students

E-learning offers the potential for flexibility and inclusivity, but its success for disabled students depends primarily on access practices and pedagogical application. While quantifiable standards have been established for the Web Content Accessibility Guidelines (WCAG 2.2), facilitating factors such as focus visibility, target size, and error prevention do not automatically ensure pedagogically inclusive content (W3C/WAI, 2024). Likewise, while Universal Design for Learning (UDL) is charged with advocating multiple means of engagement, representation, and expression to pre-assume learner variability, its practice within institutions has been uneven (Bray, 2024; Filippou et al., 2025).

While many universities have endorsed these guidelines, research shows that accessibility is still viewed primarily as a technical requirement rather than an integral part of a broader learning strategy (Lomellini et al., 2025). This gap results in disabled students continuing to encounter usability obstacles, such as inaccessible navigation, lack of compatibility with assistive technology, or cognitive overload, even when the platforms are declared compliant (Królak & Zając, 2024). Therefore, the task is no longer to meet standards but rather to interpret them into adaptive, responsive learning systems that personalize experiences by tailoring them to learners' competencies and preferences.

2.2 Artificial Intelligence in Inclusive Education

Artificial Intelligence (AI) is a transformative technology for addressing accessibility challenges and fostering inclusive pedagogy. Research has identified three main AI contributions to inclusive education: (i) multimodal accessibilities such as speech-to-text and image descriptions tools, (ii) adaptive personal learning where algorithms modulate the complexity and pace of content learnt, and (iii) predictive analytics for risk detection (Melo-López et al., 2025; Iniesto & Rodrigo, 2024). These advancements appear to be a valuable resource for overcoming barriers associated with sensory or cognitive impairments and fostering learning engagement.

Empirical evidence, however, indicates that most AI projects are limited to resource-level interventions rather than a fundamental shift (Lowenthal & Lomellini, 2023). Although automatic captioning and adaptive user interfaces (UIs) enhance access, many websites do not assess the effectiveness of learning delivered through them or tend to measure user satisfaction (Kioupi et al., 2023). Moreover, it is still underexplored to scratch the surface of the moral implications of subjects such as algorithmic prejudice, privacy, and data ethics, raising questions about justice

(Prinsloo, 2023). This literature, in turn, indicates that a more holistic infusion of AI is necessary into inclusive-education models that combine technical accessibility with documentable learning gains and risk-reduction effectiveness.

2.3 Case Studies and Risk Mitigation in E-Learning for Disabled Students

The evidence suggests that disabled students experience a range of obstacles to e-learning that can serve as triggers for disengagement or non-participation. Regarding the impact of assessment on students' decision-making, Duncan, Butler, and Punch (2025) concluded that it was often not student impairment per se but environmental and institutional topical barriers, including inflexible assessment formats and a lack of support with the technicalities, that triggered the dropout process. Likewise, Nieminen, Moriña, and Biagiotti (2024) demonstrated that rigid assessment practices and unaccommodating learning resources continue to harm disabled students in the era of institutional inclusion.

From a risk-management standpoint, such obstacles can be viewed as learning risks that require proactive mitigation. Risk Mitigation is a formal process for identifying, analyzing, and, in some cases, reducing failures before they occur (Hubbard, 2009; Rauf & Mansor, 2021). The translation of this concept into education, as seen in other fields, is that e-learning risks can be forecasted and controlled using AI-driven data analytics (Afonso et al., 2025; Alamien et al., 2023) to address issues like accessibility failures, cognitive overload, and rejection. By recognizing difficulty patterns using data, AI can create triggers for interventions that prevent dropouts and enhance engagement. Therefore, risk mitigation does not act solely as a management instrument; it also obliges to support social inclusion in digital learning.

Moreover, the advantages of e-learning, such as flexibility, cost reduction, and self-scheduling access, can be optimized when using AI-based tools that dynamically model learners' profiles (Lomellini et al., 2025). Such adaptive design has the potential to sustain participation and mitigate technology-related exclusion, with implications for inclusive education and broader digital transformation in higher education.

2.4 Theoretical Framework

Within an integrated theoretical model incorporating the Social Model of Disability (SoD), Universal Design for Learning (UDL), and Risk Mitigation Theory, the present study was established. The Social Model of Disability locates the cause of disability in environmental barriers rather than in personal impairments (Lawson, 2021). E-learning is responsible at the institutional and designer levels to eliminate systemic barriers through technology and/or policy. The pedagogical aspects of the UDL framework are connected to its concept of variability in learning design and representation, which involves learning through different modes (gesture and sign language to engage interest), engagement, or expression for a diverse audience (Bray, 2024). The Risk Mitigation Theory (Hubbard, 2009) suggests that AI can be a proactive tool for detecting, measuring, and managing learning risk through predictive analytics and adaptive interventions.

Drawing these theories together, this study begins to envision AI not simply as a technological development but as a facilitator of social inclusion (Social Model), a designer of flexible learning experiences (UDL), and a predictive risk-management system (Risk Mitigation Theory). This theoretical basis affirms this research's aims to examine the accessibility performance, risk-reduction effectiveness, and user satisfaction in AI-assisted e-learning for disabled students.

2.5 Proposed Framework

Drawing from a theoretical synthesis of the Social Model of Disability, Universal Design for Learning (UDL), and Risk Mitigation Theory, this study suggests a new framework named AI-Driven Inclusive E-Learning Risk-Mitigation Framework (AI-IERMF) that rethinks how digital learning environments foresee student disabilities and uses a proactive way to confront students with disabilities. The model presents AI as an intermediary between the status quo and a compliance-based approach towards accessibility, towards a predictive, adaptive, socially responsive inclusion. It includes five interconnected levels, each representing a single figured construct and grounded in previous research and the aims of this study.

2.5.1 Personalized Learning Adaptation (1st Layer)

By automatically providing personalized learning layers, AI-based e-learning systems lower the barrier to access for disabled students. These systems rely on machine learning techniques to assess students' levels, learning styles, and speed, which are used to create personalized content routes (Jiali et al., 2024). For instance, students with visual impairments might receive audio materials, and those with cognitive challenges might be given simplified, sequentially structured lessons. This individualised model facilitates access to education and ensures that no student is left behind, thereby answering the first research question. It also includes AI-powered recommendation systems and natural language processing to customize content, pacing, and the user interface based on learner profiles and feedback from assistive technology. This Layer reflects UDL by providing multiple means of engagement and representation (Bray, 2024; Filippou et al., 2025). Moreover, studies such as Contrino (2024) demonstrate that adaptive learning can significantly enhance engagement and comprehension, particularly for students with diverse needs.

2.5.2 Real-Time Assistive Interaction Module (2nd Layer)

To establish safe learning environments, AI-powered platforms integrate interactive assistive modules in real time. Speech-to-text, text-to-speech, and gesture recognition technologies can be integrated, facilitating easy communication for students with hearing or visual impairments as well as those with motor disabilities (Lata, 2024). These features lower cognitive load and facilitate self-directed learning by providing consistent access to content, peers, and faculty. For example, a deaf student can participate in real-time lectures using instant captions. It also leverages multimodal AI (speech-to-text, captioning, and gesture recognition) to enable real-time access and reduce cognitive load. Previous studies have shown that adaptive interfaces increase usability and motivation among visually and hearing-impaired students (Iniesto & Rodrigo, 2024; Lomellini et al., 2025). Studies by Chalkiadakis et al. (2024) indicate that real-time AI support reportedly increases students' autonomy and confidence, ultimately contributing to the development of a safer, more supportive online learning environment.

2.5.3 Social Inclusion and Collaboration Hub (3rd Layer)

However, beauty is a necessary but not sufficient condition for use and social inclusion/access. AI-enabled e-learning spaces foster accessibility by creating collaborative centers that support alternative forms of communication (e.g., voice-to-text forums, AI-moderated discussion boards). The centers also offer students with special needs the chance to learn together in groups, which promotes social connections and decreases feelings of isolation. Further, they employ AI-powered analytics to encourage equitable participation in forums and group activities, ensuring participatory networks are equitable and inclusive. This is consistent with the tenets of the Social Model of Disability, which focuses on addressing social and institutional obstacles (Lawson, 2021; Kioupi et al., 2023). Peer interactions improve performance and motivation, thereby enabling disabled students to share a sense of belonging (Kovari, 2024). In this way, the third research question regarding increased accessibility and engagement is met by ensuring that students have meaningful interaction with peers.

2.5.4 Risk Detection and Mitigation System (4th Layer)

AI-based platforms continuously monitor engagement data, performance outcomes, and behavioral cues to identify early signs of academic dissonance or disengagement. The risk reduction system triggers personalized actions on the learner's side, such as pacing adjustments, content simplification , or teacher notification. This is an auto-disengagement system that uses predictive analytics to detect trends of disengagement, low activity, or connectivity issues. Informed by Risk Mitigation Theory (Hubbard, 2009), the platform presents risks in a language most understandable to them. It offers individualized avenues of mitigation such as auto-reminders, plain-language resources, and invitations to peer support (Afonso et al., 2025; Ichsan et al., 2024). Thus, it helps reduce school dropouts and supports troubled students before they fail (Embarak & Hawarna, 2023). For instance, an AI system might recognize that a student with dyslexia misreads some material several times and swiftly provides audio alternatives. These systems keep learning safe and open, thus addressing the second inquiry on developing low-risk fields of learning.

2.5.5 Policy and Compliance Integration (5th Layer)

This Layer will help ensure that WCAG 2.2 technical standards and national inclusive-education policies are adhered to by delivering real-time compliance dashboards and audit trails. This also facilitates development and evidence-based decision-making (W3C/WAI, 2024; Prinsloo, 2023). It also guarantees that the adapted content and auxiliary instruments will continue to exist and be updated (Lowa, 2024). Moreover, AI is used to assist authorities in analyzing data on how students are performing and engaging with learning, enabling evidence-based changes to support models. This alignment safeguards the development of inclusive education alongside technological advancements, thus supporting sustainability and further strengthening all three research questions.

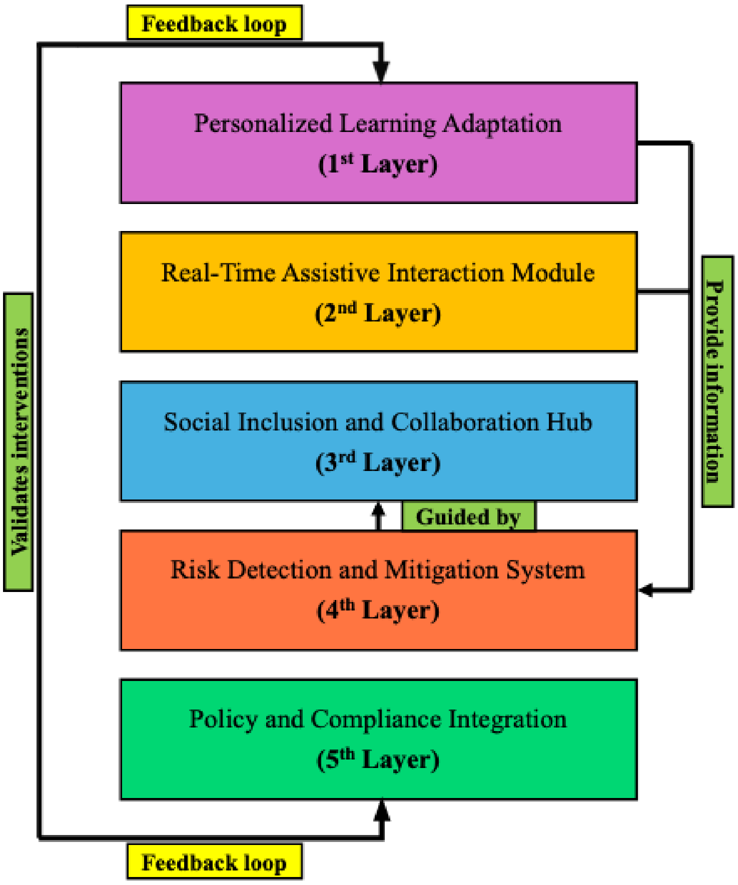

Fig. 1. Proposed Framework

Finally, this AI-IERMF is a closed-loop, adaptive system in which the learner's data flows through layers. Accessibility data (First and Second Layers) then provides information to the risk-detection algorithms (Fourth Layer), which, in turn, trigger pedagogical or technical adjustments via the adaptation layer. Engagement risk scores are guided by social-interaction analytics (Third Layer), and the compliance layer (Fifth Layer) validates all interventions against institutional and ethical guidelines. Feedback loops create a self-learning cycle that gradually refines inclusivity and learning effectiveness.

3. Research Method

This section describes in detail the entire research process. Furthermore, all research steps must be presented in a step-by-step, comprehensive flowchart or framework that covers the reflected algorithm, rules, modeling, design, and other system components.

3.1 Research Design

A qualitative, multiple-case study in a phenomenological design was conducted to investigate how AI-mediated e-learning platforms help reduce learning risks and increase accessibility for students with disabilities. This study took a qualitative research approach to retain the nuanced and multifaceted nature of experiences, extending beyond numerical measurements by examining meaning, interaction, and perception (Creswell & Poth, 2018). While most quantitative methods tend to focus on numerical outcomes, qualitative research documents the rich texture of social life, making it particularly well-suited to examining the subtler issues faced by disabled students (Merriam & Tisdell, 2016). In addition, this study draws on phenomenological perspectives to gain insights into the lived experiences of disabled students in an AI-enhanced e-learning context (van Manen, 2016). This design aligns with the study's aims to build pragmatic, user-centred knowledge for inclusive e-learning design.

Other than that, according to Yin (2018) and a multi-case design, each case should be considered a bounded system depicting a particular institutional context. The phenomenological approach guided questioning about how students experienced access, utility, and inclusivity. This enabled within-case analysis (individual context) and cross-case comparison (thematic synthesis), producing findings that were situated yet also generalizable at the analytic level.

3.2 Case Study Contexts and Sampling Overview

Three Malaysian universities were purposively chosen as cases to depict different levels of online readiness and inclusiveness. Aligned with institutional ethical standards and to ensure the anonymity of participants and sensitivity of institutions, we refer to the universities involved as University A (a research, intensive public university that already has a digital infrastructure in place), B (a mid-tier comprehensive university that is still in the midst of transitioning to hybrid AI-supported teaching) and C (private university acting as an early adopter for adaptive learning analytics). The tri-case design targeted literal replication (the answer to the same question across three sites) and theoretical replication (to understand differences due to context that enrich interpretation) (Yin, 2018). This rich depth and breadth enhanced the internal validity and transferability of the findings.

3.3 Setting

All three universities work within Malaysia's national policies for inclusive education and use mainstream learning management systems (LMS), which are Moodle and Blackboard. Their use of AI features differs, with some deploying auto-captioning, translation, and personalized dashboards, while others emphasize manual method adjustments. The study took place from January to June 2025, and ethical clearance was obtained from the Research Ethics Committee of the Host University. Fieldwork was conducted in computer-assisted labs and online virtual environments, enabling the researcher to observe learners' interactions with AI features as they unfolded in real time under natural learning conditions.

3.4 Participant Details

The participants included 34 individuals: 25 students (8 with visual impairments, 10 with hearing impairments, and 7 with mobility impairments), aged 18-25, who were part-time students at undergraduate and postgraduate levels; five e-learning developers; and four instructors involved in accessibility. Sampling approached a purposive, maximum variation design, oriented to represent different experiences across disability types and academic disciplines (Palinkas et al., 2015). All students had experience using AI-supported e-learning tools for at least a semester. At the same time, instructors and developers were chosen because they were directly involved in inclusive course delivery or system design. Participation was voluntary, and consent was confirmed through available digital formats such as screen-reader-accessible PDF forms and simplified summaries.

3.5 Data and Instruments

Semi-structured interviews were undertaken, along with focus group discussions and non-participant observation. The interview guide prompted participants to elaborate on their experiences with AI-based learning features such as adaptive text simplification, automatic captioning, and voice-command navigation. The semi-structured interviews provided some flexibility, allowing the researcher to explore emerging ideas without repeating topics across participants (Kvale & Brinkmann, 2015). In focus group activities, participants were encouraged to make sense of the material collectively and to share common accessibility problems. Observations also recorded AI interface use, including students' real-time interactions with the interfaces, how they sought content and navigated within it, how they managed cognitive load demands (some had high-level reading, writing, or counting impairments), and how they used support aids. Two accessibility experts were consulted and approved each instrument for linguistic clarity and disability context sensitivity. All sessions were held via Zoom, with captioning and assistive technology to promote equitable access.

3.6 Selection Criteria for Literature and Case Studies

The literature informing this study was limited to peer-reviewed articles from journals currently published (from 2020 to 2025) and only articles indexed in Scopus or the Web of Science for currency and international relevance. Search terms used were "AI," "inclusive education," "disabled students", "accessibility," ¨UDL", and "e learning risk mitigation". The relevance of the publications was determined by the conceptual relationship to the accessibility of WCAG 2 and the UDL framework.

In terms of the empirical part, case-study institutions were selected with reference to three clear criteria: (1) each having an active disability support unit and enrolment population of students with registered accessibility requirements; (2) actions in place or in development to trial at least one AI-enabled learning or analytics platform; and (3) provision of institutional consent for obtaining participant details as well data gathering. They were developed to ensure that the site selection was both information-rich and reflective of the changing landscape of digital inclusion in Malaysia.

3.7 Data Collection Procedures

Data collection occurred across three consecutive phases. During the exploratory phase, the researcher worked with home coordinators to develop research tools and identify appropriate participants. The primary phase was composed of individual interviews lasting 30–60 minutes, followed by focus groups consisting of five to six participants for each group. All interviews were audio-recorded, transcribed in full, and anonymized. Observational data were collected from real e-learning sessions to model participants' use of AI tools, including caption generators and chat assistants. During the validation process, preliminary results were briefly shared with participants to verify accuracy and interpretation. Ethical and accessibility considerations, such as voluntary participation, confidentiality, and compliance with data protection regulations, were adhered to throughout.

3.8 Data Analysis

The analysis adopted a reflexive thematic analysis method, as articulated by Braun and Clarke (2023), using NVivo 14 to organise and code qualitative data. The method included repeatedly diving into the data, generating initial codes, collating codes into potential themes, and refining them to fit the transcripts through cross-case comparison. Six procedures for analysis were applied: familiarization, coding, theme discussion, definition, and synthesis. These themes were then charted against the conceptual framework developed for the study, which includes Accessibility Performance, Risk Reduction, and User Satisfaction, with a view to identifying cross-cutting and counter-cutting case patterns. The researcher's reflexivity was assured through memo writing and peer consultation to foster transparency and in-depth understanding.

3.9 Validation and Triangulation Framework

The trustworthiness of the study was assessed against the criteria of Lincoln and Guba (1985), comprising credibility, dependability, confirmability, and transferability, as a validation regimen to ascertain methodological rigour. Multiple triangulation strategies were integrated. Evidence from interviews, focus groups, and observations was compared using data triangulation to explore convergence and divergence. Investigator triangulation consisted of two qualitative researchers who examined coding products and the congruence of themes. Participants were allowed to check transcripts for accuracy and interpretation (Birt et al., 2016). An audit trail of analytic decisions, coding frameworks, and reflexive notes maintains transparency (Creswell & Poth, 2018). Last, peer debriefing with experts in AI and inclusive education helped validate preliminary interpretations and reduce researcher bias. Taken together, these strategies ensured methodological rigor and enhanced the reliability of the study's conclusions.

4. Results and Discussion

4.1 Empirical Findings Across Case Studies

Common and context-specific patterns emerged across the three Malaysian universities investigated regarding their embrace of AI-enhanced inclusive e-learning. Data analysis yielded four primary themes: increased access through AI-facilitated adaptation, enduring usability and trust issues, greater learner agency, and institutional differences in preparedness for implementation.

At University A, the implementation of automatic captioning and text-to-speech features led to a marked improvement in comprehension for deaf and visually impaired students. "*Since this AI captioning tool was established, I can have class without needing to ask my classmates or friends to repeat what the lecturer says*," one participant (P12, hearing impairment) reported. Archives of institution documentation (A) indicated that assignment completion rates by disabled students increased from 68% to 82% within a single semester. Similar evidence of increased completion and retention has been found abroad with captioning and AI-assisted reading tools (Desai et al., 2025; Rojas et al., 2023; Siregar & Putra, 2023).

At University B, with partial AI integration, varied accessibility improvements were noted. Inconsistent caption quality and translation errors were reported among participants in mixed-language lectures: "*Some of the time, AI translates nonsense when the lecturer mixes up English language with Malay language*," participant P4 stated. A parallel problem of multilingual captioning errors has also been reported in European (Lomellini et al., 2025) and Asian languages (Palancı et al., 2024; Purwati et al., 2023).

In the case of University C, on the other hand, a higher level of user satisfaction was observed. Students said they were "*feeling more in control*," while instructors enjoyed early-warning analytics that identified disengagement. These results align with global trends, where adaptive dashboards enhanced motivation and feedback loops (Bergdahl et al., 2024). Nonetheless, questions concerning the non-transparent algorithmic logic of the system remained: "*I do not know how the system determines what I need to learn next, and this makes me uneasy*" (P23; visual impairment). The above trust asymmetry is similar to that found by Liu et al. (2023) in their privacy-centric study of learning analytics.

4.2 Comparative Insights: Before and After AI Integration

Compared with AI unleashing, participation and academic continuity increased significantly after AI implementation. Prior to integration, faculty used accommodations such as printed transcripts or peer note-taking. Upon deployment, blind students could access resources independently via text-to-speech and image description tools, whereas mobility-impaired students benefited from voice-command navigation. These findings align with international research indicating that generative AI tools promote learner agency and self-paced learning (Pierrès et al., 2024; Melo-López et al., 2025). However, differences persisted, with institutions with weaker digital conditions experiencing slower performance, thereby diluting the benefits AI can provide (Palancı et al., 2024), clearly indicating that inclusion outcomes could depend on institutions' levels of digital maturity and system upkeep (Fitas, 2025; Kusdiana et al., 2024).

4.3 Ethical and Technical Challenges

While AI personalization makes systems more inclusive, it raises serious ethical and technical questions. Algorithmic bias can unintentionally marginalize underrepresented learners who are not represented in privileged datasets when the training data lacks diversity in disability representation (Baker & Hawn, 2022; Narimawati et al., 2023). This was a problem with captioning algorithms for regional dialects. Related algorithmic fairness challenges have come into focus in the broader educational data landscape (Liu et al., 2023). Participants also wondered how their analytics were stored and used, reflecting widespread concern about consent and transparency in AI learning environments (Melo-López et al., 2025; Pierrès et al., 2024). In practice, captioning accuracy and real-time transcription are not perfect, especially in multilingual classrooms, where latency hinders classroom participation (Desai et al., 2025; Rojas et al., 2023). Studies have indeed confirmed that algorithmic captioning still needs human editing to ensure educational reliability (Lomellini et al., 2025). Hence, inclusive AI must be embedded within strong governance frameworks that include considerations of ethics and oversight, algorithmic transparency, and user responsiveness mechanisms (Filippou et al., 2025; Wahyuni et al., 2025).

4.4 Feasibility in Low-Resource Contexts

Sustainability of AI integration, in terms of feasibility, was an important factor. At University B, bandwidth restrictions also caused delays, eroding the flow of synchronous access: "*Sometimes the captions come up after the lecturer has already changed slides*," one student complained. These infrastructure constraints mirror those found elsewhere in the global South, where connectivity and hardware inequalities continue to inhibit the adoption of inclusive technologies (Fitas, 2025; Navas-Bonilla et al., 2025). The institute's readiness and funding were also factors contributing to the results. The success of the private university stood in stark contrast to public institutions, which struggled with limited technical staff and budgets, findings that echo research on global patterns showing that institutional support predicts effective AI adoption (Bergdahl et al., 2024; Palancı et al., 2024). For these reasons, scholars also suggest a gradual adoption of technologies, such as open-source, bandwidth-light tools, to avoid the digital divide (Fitas, 2025; Liu et al., 2023).

4.5 Comparative Perspective with Existing Inclusive Models

Conventional frameworks like UDL and WCAG 2.2 focus on design coherence and accessibility conformity, but not on adaptive intelligence. The adaptation of the aforementioned models is furthered with the AI-Driven IERMF, which enables massive risk mitigation through predictive analytics and automated feedback loops. Where UDL centers different ways of representation and engagement (Rose & Meyer, 2022; Yanti et al., 2023), the AI-IERMF provides dynamically adjusted representations in response to learning data as they occur in time, resonating with modern proposals for pledging inclusion toward mechanisms that respond to data recording the process of people interacting and learning (Lomellini et al., 2025; Filippou et al., 2025). Recent international overviews stress that developing inclusive policy must be combined with AI-backed adaptation to shift from reactive accommodation to proactive personalization (Melo-López et al., 2025; Navas-Bonilla et al., 2025). Evidence from this study supports the progression of that approach whereby the AI-IERMF puts inclusion into action by integrating risk-detection analytics to predict accessibility breakdowns, moving beyond static compliance models used by conventional design frameworks toward continuous quality-assurance improvement.

Taken together, these results suggest that AI-driven technologies have the potential to make a significant impact on access, engagement, and sustained learning for students with disabilities when deployed within ethical, transparent, and appropriately resourced ecosystems. They also establish international consensus on the importance of successfully integrating context adaptation, stakeholder engagement, and continuous feedback across policy, pedagogy, and technology (Hutahaean et al., 2023; Lomellini et al., 2025; Navas-Bonilla et al., 2025).

Drawing on global research and generalizing across cases, the study finds that AI integration in inclusive e-learning best results from three mutually reinforcing principles, which are ethical design (ED), adaptive personalization (AP), and infrastructural preparedness (IP).

These precepts position the AI-IERMF as both an international model for bridging the gap between high- and low-resource educational systems.

5. Conclusion

This study shows that ethical design, adaptive personalization, and infrastructural preparedness can effectively mitigate learning risks for disabled students through AI-enabled inclusive e-learning ecosystems. AI, as evidenced in the 3 Malaysian case studies, comprised automatic captioning, predictive learning analytics, and text-to-speech engines, which supported participation, understanding, and interaction. The results are consistent with international evidence that technology-based personalization enhances digital inclusion and learner autonomy. However, this study also acknowledges structural limitations, which a visit to only a small number of institutions impedes generalization beyond those institutions, and qualitative data might not capture all intersectional experiences of disability.

Future studies should thus confirm these results in larger samples, using mixed-methods across institutions, and investigate integration of AI at a variety of educational levels, from primary to higher education. Expanding the model to other multimodal accessibility tools, such as AR/VR environments, haptic feedback-based environments, and emotion-sensory interfaces, could further enrich participation beyond cognitive acclimatization. Cost-benefit analysis is also required to evaluate sustainability and scalability in low-resource settings.

6. Recommendations and Implications

To bridge the gap between research insights and practice, this study urges policymakers to institutionalize funding for accessibility audits of assistive technology infrastructure and for the WCAG 2.2 and UDL frameworks. Educators are expected to attend continuous training sessions to design pedagogical and assessment systems based on adaptive technologies that respond to different learning profiles. Platform designers and developers should incorporate a participatory co-design mechanism that engages disabled users at every stage, from prototyping to deployment, emphasizing transparency and fairness in algorithms.

The real-world impact is a roadmap towards proactive rather than reactive accessibility-by-design in AI systems. Theoretically, this means broadening the social model perspective on disability into a predictive-risk framing in which AI is not just seen as a support technology but also as an instrument of systemic change.

All in all, the future of AI-enhanced inclusive e-learning is at the crossroads of ethics, equity, and engagement. By addressing infrastructure imbalances, offering user-centered co-design, and sustaining continuous evaluation, institutions' systems can shift from compliance-based, inaccessible systems to a culture of digital empowerment, in line with the global vision for inclusive, barrier-free learning for all.

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