# AI-DRIVEN TEACHING: EXPLORING THE POTENTIAL OF AI(LLM)-BASED EVALUATION FOR MOODLE IN THE INDIAN EDTECH MARKET

by

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## Dedication

I dedicate this dissertation to my parents, whose constant encouragement has always driven me to pursue higher education. To my wife, my life guide and problem solver, whose unwavering support and wisdom have kept me focused throughout this journey. And to my young son, whose arrival gave me both the inspiration and determination to take up this doctoral challenge and see it through.

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ABSTRACT

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The adoption of Artificial Intelligence (AI) in education is transforming digital learning environments, with Learning Management Systems (LMS) such as Moodle emerging as key platforms for AI-driven teaching and assessment. This study examined the integration of Large Language Models (LLMs) in Moodle, with a focus on the perceptions, usability, and effectiveness of educators and students within Indian educational contexts. A survey of 125 respondents, including educators, administrators, students, and Moodle developers, was conducted to collect quantitative data on usage patterns, perceptions of AI effectiveness, grading consistency, and LLM integration needs. Descriptive statistics, ANOVA, correlation, and Chi-square tests were employed to analyse the data. Key findings reveal that respondents perceive AI tools as moderately effective in addressing student evaluation needs ($M = 3.49$) and LLM-based grading as consistent compared to manual methods ($M = 3.57$). The importance of local content customisation ($M = 3.52$) was also highlighted. ANOVA results indicate significant differences in perceptions of AI effectiveness across user groups, while LLM grading consistency was viewed uniformly. Correlation analysis showed a significant positive relationship ($r = 0.470$, $p < 0.01$) between personalised LLM features and the need for local content customisation. Chi-square analyses revealed that perceptions of LLM scalability are influenced by manual grading challenges ($p = 0.006$) but not by Moodle usage experience ($p = 0.944$). No significant differences were observed regarding the perceived requirements for effective LLM integration across respondent roles or Moodle experience. The research found that LLMs can provide greater consistency in grades, personalised feedback to students, and scalability within the educational system, but adoption requires school infrastructure and teacher training. The implications related to contextual, localised AI solutions that can be integrated within Indian classrooms. The study suggests the need for structured professional learning opportunities for teachers, phased implementation of LLMs into classrooms, and a consideration of the policy context for educators to engage ethically and responsibly with inclusive and useful AI within the educational setting.

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List of Abbreviations

| Abbreviations | Full Form |
|---|---|
| AI | Artificial Intelligence |
| LMS | Learning Management Systems |
| LLMs | Large Language Models |
| NEP | National Education Policy |
| BBS | Bulletin Board Systems |
| WWW | World Wide Web |
| MOOCs | Mass Open Online Courses |
| MOODLE | Modular Object-Oriented Dynamic Learning Environment |
| CAI | Computer-Assisted Instruction |
| VR | Virtual Reality |
| NLP | Natural Language Processing |
| SFT | Supervised Fine-Tuning |
| SRs | Systematic Reviews |
| BERT | Bidirectional Encoder Representations from Transformers |
| GPT | Generative Pretrained Transformer |
| CLT | Constructivist Learning Theory |
| PEOU | Perceived Ease of Use |
| PU | Perceived Usefulness |
| TAM | Technology Acceptance Model |
| CoT | Chain-of-Thought |
| AGI | Artificially Generated Intelligence |
| OLE | Online Learning Environment |

| | |
|---|---|
| KSMA | Kherson State Maritime Academy |
| CBEs | College of Business Education |
| CT | Connectivism Theory |
| CNNs | Convolutional Neural Networks |
| TCCM | Theory-Context-Characteristics-Methodology |
| SVMs | Support Vector Machines |
| SPSS | Statistical Package for The Social Sciences |
| ANOVA | Analysis of Variance |

# Chapter I:
# Introduction

## 1.1 Introduction

The rapid evolution of digital technologies in the recent past has also hugely affected the educational situation world over and online learning platforms have found their way into the teaching and learning process. This change has been particularly significant in India, owing to factors such as the entry of smartphones, surging internet connectivity, and government initiatives, such as Digital India and the National Education Policy (NEP) 2020. The EdTech industry in India has experienced unparalleled growth that gives convenient and flexible learning opportunities to different learners in rural and urban regions (Goyal et al., 2025a). LMS such as Moodle has become the most favoured solution in this ecosystem in terms of delivering well-structured content, administration of assessments and tracking student progress. Despite the comprehensive nature of Moodle as an online learning platform, one problem has never been addressed by Moodle: how to assess the performance of the students. Traditionally used methods of evaluation tend to be time-consuming to the teacher, not scalable to large groups, and subjective, which limits their applicability in delivering fair and personalised learning results (Yan et al., 2024).

LLMs and AI can help address these evaluation problems. The LLMs can process and interpret natural language and, therefore, can measure complex and open-ended student responses that are not restricted to simple multiple-choice and objective questions (Impey et al., 2025). With the direct use of LLM-based assessment tools within Moodle, it is possible to automate the grading process and guarantee its high rigor and accuracy in judging the quality of the work, which is impossible due to human evaluation (H. Li et al., 2025). Moreover, the models can generate personalised feedback that would say what strengths should be worked on, what areas should be improved, and what positive suggestions should be made to continue learning (Caines et al., 2023). This power to support adaptable learning pathways helps students to progress their learning requirements by making education more student-friendly. Beyond that, automation can increase the efficiency of the work of educators by relieving them of some of the burdens, and this will help teachers devote more time to other teaching-related activities, which are more advanced instructionally, such as mentoring, curriculum design, and fostering critical thinking skills in their students (Chiang, 2023); (Moodle, 2023).

Besides enabling a more accurate and efficient evaluation, the implementation of LLM-based evaluation systems in Moodle can change the performance and engagement of learners at scale. These models have the potential of helping to help identify at-risk learners of disengagement or drop-out by continued analysis of the trends of student performance and participation. By identifying at-risk students at an early stage, it is possible to intervene by providing one-on-one academic tutoring, having them join peer groups, or any other form of motivation that can help those who are at risk to remain on track and achieve higher success (Solutions, 2023). This is especially true in the case of India, where there is no differentiation possible in a common education system due to student-to-teacher ratios and diversity of students (Goyal et al., 2025b). Therefore, integration of LLM-based assessment tools in Moodle could not only fill the current gaps in the field of assessment but also help meet the objective of equity, accessibility and quality improvement in the Indian EdTech world (Yan et al., 2024).

In view of these changes, it is apparent that the incorporation of evaluation tools based on LLM into Moodle can transform the Indian EdTech market. However, even though there is international experimentation and growing curiosity as to how this can be used to evaluate students, the issue of adoption in India has not been extensively examined and particularly not on the open-source learning platform, Moodle. This establishes a sense of necessity to investigate them regularly in terms of their viability, their effects and their adaptability to contexts. Hence, this research aims to investigate the potential of efficiently utilising LLM-based evaluation in Moodle to make assessments more accurate, personalised, and efficient in the context of India. By critically discussing the opportunities and challenges of AI in education, the study will add to the current knowledge base of AI in education and offer practical suggestions to policymakers, educators, and EdTech innovators on how to create a more inclusive and smarter learning environment.

**The Rise of Moodle in Indian EdTech**

Numerous facets of modern life rely heavily on technological advancements. Efficiency has been greatly enhanced as a result of the substantial simplification and acceleration of activities (Raja & Nagasubramani, 2018). Technology has brought about enormous changes across several sectors, including education, demonstrating its unquestionable importance in modern life. Both students and educators have benefited from the increased efficiency and engagement brought about by technological advancements in the classroom. It enhances education by creating personalised learning experiences, improving engagement and motivation, and facilitating collaboration between students and teachers (Kathleen, 2016); (Rajabovna & Salahiddinovich, 2024); (Sumakul et al., 2024).

The Learning Management System (LMS) is a leading example of how technology is being used in education. Learning management systems (LMS) enable the creation, dissemination, management, tracking, reporting, and assessment of online instructional resources (Mershad & Wakim, 2018); (Permana, P. (2009). E-Learning, 2009). Moodle, an acronym for "Modular Object-Oriented Dynamic Learning Environment," is a widely used open-source platform for online education. Users can create a private course website that is accessible only to enrolled students, and Moodle offers various features such as forums, quizzes, and resource sharing to make online courses more engaging and interactive (Cole & Foster, 2007). The tool allows individual teachers to be more creative in designing customised teaching modules for students. Moodle, developed by Martin Dougiamas at Curtin University, Australia, has evolved into a flexible platform that saves educators' time through features such as automated testing, scoring systems, and constructive feedback tools. Early studies highlighted its potential to improve learning efficiency (Nedeva, 2005; Rosato et al., 2007), while more recent research emphasizes its capacity to enhance assessment quality and student engagement (Aljawarneh, 2020; Gamage, Ayres, & Behrend, 2022). Moodle also facilitates collaboration between students through online group assignments and interactive discussions, which is highly relevant in improving speaking, writing, and vocabulary acquisition in foreign languages (Brandl, 2005); (Qaddumi & Smith, 2024).

Online learning outcomes for students have been improved with the help of educational data mining techniques (C., 2024). The realisation that not all critical data is saved in one data stream is the best development for educational data. Several innovative improvements to education have resulted from research in the field. Changes to their daily life have been wrought by advancements in computer technology. Results from these accomplishments are now helping to fuel a second round of change across all industries and educational institutions.

There are usually numerous unexpected but confirmed hierarchical layers in any given piece of information, says the International Educational Data Mining Society (2011). Research in the field of education takes into account the elements of time, order, and setting. It is possible to examine the following student data: engagement, login frequency, chat messages, and question types (Dutt et al., 2017). All data collection is subject to the discretion of the online learning platform. It is impossible to track how long it takes students to finish exams if the database of the online learning platform does not include time variables. What EDM can and cannot do with data is dictated by the online learning platform. To tell the truth, online learning systems are still mostly a product of machine learning's design process.

According to (Allen et al., 1974), One of the biggest challenges in teaching second languages is keeping students' interest and participation in class. Research by (Krahnke & Krashen, 1983), MacIntyre, R C Gardner suggests that teachers should consider students' motivation, anxiety, and self-confidence as important aspects of the learning process. The goal of gamification design in SLA settings is to engage all students in a game-like atmosphere by incorporating elements that drive different types of players. Building on self-determination theory, Dehghanzadeh et al. (2019) argue that gamification motivates learners by appealing to psychological needs such as autonomy and competence. While its motivational effects are well documented, Cardoso et al. (2017) and Dehghanzadeh et al. (2019) point out that the cognitive benefits of gamification in second language acquisition (SLA) remain underexplored. This gap suggests a need for more empirical studies on how gamification influences deeper learning processes, beyond motivation alone.

An assortment of LMSs is at your disposal for creating, organising, and disseminating digital materials for both online and in-person instruction. Personalised online learning opportunities for students are made possible by the integration of digital learning resources with more conventional methods of instruction through an LMS (Aljawarneh, 2020). Since the COVID-19 pandemic began in 2020 and severely curbed in-person instruction in many schools around the world, online education has become increasingly popular (Dias et al., 2020); (Raza et al., 2021). Because of physical contact limits, schools have had to change the way they teach, evaluate, do research, and discuss scientific topics. With the proliferation of high-speed internet and other innovations in online education over the past decade, LMSs have become increasingly important in STEM (Science, Technology, Engineering, and Mathematics) curricula. Numerous schools have found success with LMSs, and more and more are devoting resources to studying which LMSs work best.

The term "online education" refers to a hybrid approach to learning that combines elements of both traditional classroom instruction and independent study by placing course materials and student-led discussions on the Internet and encouraging students to engage with one another through the sharing of relevant knowledge and resources (Gil, 2015). Teachers' primary responsibility in this model of remote learning is to foster greater student engagement, enthusiasm, and ownership of the learning process. (Majeed et al., 2021); (Al-Malah et al., 2020) state that in modern classrooms, teachers are no longer merely information disseminators and consumers, but also designers and organisers of learning experiences. In order to achieve this goal, teachers must first plan and implement lessons, determine how students will learn, and then manage class discussions, assignments, and other forms of student-teacher communication in order to promote online learning (Rapanta et al., 2020).

**Need for AI-Based Evaluation in Digital Education**

With the rapid advancement of digital learning platforms, the traditional methods of student assessment are being re-evaluated to meet the evolving demands of modern education (Dritsas & Trigka, 2025). When it comes to accuracy, efficiency, and personalisation, the use of AI in educational assessments is a game-changer. Educators can evaluate their students' progress and identify areas for improvement with the use of AI-powered assessment tools that process massive amounts of data about them in real-time. This growing demand suggests the shift towards more adaptive, data-driven, and learner-centred models within online education (Gligorea et al., 2023).

AI is a technology that has transformed most sectors, including education. The use of I is becoming common in the classroom to deliver personalised learning solutions, as well as to streamline administrative processes (Vieriu & Petrea, 2025a). AI might be used to analyse and process massive amounts of student data, provide students with personalised feedback on their learning progress, and customise course materials to each student's needs. Through the provision of personalised learning experiences, it can also positively affect students' academic accomplishments (Makhambetova et al., 2021). On top of that, by automating some of the administrative tasks, AI can free up the educator to focus on teaching and student interaction. However, using AI in the classroom is not without its complications. One of the biggest obstacles is ensuring that AI is using high-quality data. The reliability of instructional suggestions and student comments could be compromised by biased or inaccurate data. Another concern is the safety and confidentiality of student information, especially in relation to the use of machine learning tools (Pikhart & Al-Obaydi, 2025). Also, there are ethical and social concerns related to the use of AI in education. A study published in the Ethics and Information Technology study pointed out that AI in education will further increase the equity divide among students, since students with access to AI-advanced technologies will have an advantage over students without it (Bostrom & Yudkowsky, 2014). Criticism also surrounds how AI will affect the place of the educator and person-to-person communication within the classroom.

Personalised learning and increased administrative efficiency are two ways in which artificial intelligence (AI) can revolutionise the educational system. To guarantee the long-term success of AI in education, it is crucial to solve the obstacles and limits that come with it (Divyshikha et al., 2024). To resolve social and ethical issues with AI in the classroom and to enhance the data quality used by AI, additional research and development are necessary.

Over the past several decades, online education has been steadily growing in popularity. Few schools had fully formed digital learning models in place prior to the COVID-19 epidemic, and when they did, they were either haphazard or only partially integrated with more conventional forms of instruction (Laufer et al., 2021). After the pandemic's devastating effects, the education industry and teachers in particular had to quickly adopt digital solutions to keep teaching and learning going. Online LMSs (e.g., Echo) and platforms like Zoom, Google, Teams, and interactive whiteboards have made the transition to online instruction at the most basic level possible. Whether in a more conventional classroom setting or in the context of an organisation's internal training programs, digital learning has become an integral aspect of the educational environment. When it comes to digital learning, one of the biggest obstacles that aspiring educators must overcome is the ability to evaluate not only the breadth but also the depth of their students' knowledge and comprehension. The assessment process is also carried out within the framework of the cohort and the appropriate learning band or level. According to the Australian Capital Territory Government's Teachers Guide to Assessment (Schellekens et al., 2021)The assessment process poses unique challenges for educators and learning designers. However, new technologies offer great promise for improving information gathering and learner feedback, which could revolutionise digital teaching and learning. Educators will be able to use AI to build learning materials, personalise those materials for each student, and react to data derived from student performance and comments (Cope et al., 2021). AI has the potential to greatly assist educators in providing students with rich, individualised learning experiences.

The fast development of information device hardware and software for their operation and management has led to EdTech's numerous applications in improving the quality and quantity of instruction (Mena-Guacas et al., 2025). Specifically, there has been a lot of buzz about artificial intelligence (AI) in education lately. Depending on the level of technology, AI is being used in a variety of ways, including personalised learning based on learner characteristics, interactive systems, learning and inquiry support, analysis of student writing, and intelligent agents (Tomczyk & Fedeli, 2022); (G.-J. Hwang et al., 2020). The university curriculum is also impacted by these developments, with the usage of adaptive teaching approaches and personalised learning taking into account students' learning contexts growing (E. Hwang & Shin, 2021); (Vignare et al., 2020). In the lecture field, where students take these classes for different majors and have varying levels of experience and knowledge in the subject matter, this is being tried as a substitute for traditional teaching and learning methods in order to address the demands of the teaching and learning process, such as closing the achievement gap and enhancing fundamental academic skills.

A technological civilisation is rapidly emerging as a result of developments in computer science and digital technology. In this society, robots are increasingly being built and developed to fulfil human wants while also enhancing their intelligence. Along with other promising technologies like robots, virtual reality, 3D printing, and networks, AI is expected to be a game-changer in the years to come (UNESCO, 2024); (Chai et al., 2020).

Although no universally agreed-upon definition of AI exists, it is generally understood to be the combination of artificial intelligence (the ability to learn, to derive concepts from data, and to deal with ambiguity in complicated situations) and artificial processes (those created by machines rather than occurring naturally) (Cugurullo, 2020). And lastly, the author draws the conclusion that AI is "an artefact able to acquire information on the surrounding environment and make sense of it, in order to act rationally and autonomously even in uncertain situations". (Cope et al., 2020); (Korteling et al., 2021). Drawing parallels between AI and humans is intriguing. This perspective is viewed as anthropocentric by these writers due to their belief that it is incorrect to define AI in relation to human intelligence (Korteling et al., 2021b). "The fact that humans possess general intelligence does not imply that new, inorganic forms of general intelligence should comply with the criteria of human intelligence," they write, arguing that AI is best understood as "the capacity to realise complex goals" rather than as a characteristic exclusive to humans. These aspects are crucial to the distinctions between the two forms of intelligence: fundamental framework (biological vs. digital systems); processing speed (computers are faster than humans); connection (AI systems can quickly and easily upgrade or scale up); and last, scalability and updatability. And power usage (González-Calatayud et al., 2021)

From the Middle Ages to the present day, the educational system has gone through an incredible transformation, mirroring changes in society, new technologies, and shifting pedagogical ideas. The education environment has experienced significant changes; however, there are still obstacles to overcome. It was once marked by basic teaching techniques, restricted access, and a strict curriculum (Manna & Sett, 2024). Historically, religious institutions were the mainstays of the medieval educational system, which placed a premium on rote memorisation, classical literature, and theology. Pedagogical practices based on tradition and conformity meant that access was mainly reserved for the upper classes. Personalised learning, greater access to technology, and democratisation are all hallmarks of today's educational landscape. Studying chatbots sparked the idea of making teaching avatars powered by artificial intelligence. (Weizenbaum, 1983) described ELIZA, an early chatbot-based computer program that relied on keyword analysis and decision rules to facilitate conversation through text input. Many consumers were led to believe they were conversing with a real person when they dealt with chatbots that adhered to such basic rules. The introduction of A.L.I.C.E., the first chatbot powered by artificial intelligence, in 1995 was another landmark event (Shawar & Atwell, 2015).

Because its knowledge base was modifiable, this chatbot was able to import a large corpus of natural language. Users were further convinced that the chatbot was human-like because of this stage, as it seemed to comprehend their questions and respond appropriately. The majority of chatbots, particularly those in the education industry, stuck to text-based interactions and used basic algorithms even after these early triumphs (Smutny & Schreiberova, 2020a). Modern large-language models (LLMs) can trace their ancestry back to AlexNet, which was published in 2012 (Krizhevsky et al., 2017). The model, which relied on a backpropagation-trained neural network, performed admirably in classification tasks. Chatbots built on neural networks proliferated in the years that followed, and LLMs with comparable designs were widely used (Smutny & Schreiberova, 2020b). As a result, LLM GPT4 and ChatGPT, its chat-based interface, were extensively used by the public in 2023. Afterwards, a large amount of capital was invested, which led to additional advancements in artificial intelligence. Modern LLMs, such as GPT4, are capable of exploring the web, performing admirably on a variety of cognitive tasks, and interpreting different kinds of unstructured data (Kung et al., 2023).

The empirical data on chatbots' efficacy in the classroom are encouraging. According to (Berger & von Garrel, 2022), artificial intelligence (AI) is a game-changing technology that might revolutionise whole markets, industries, company operations, and models. With the launch of ChatGPT in November 2022, the subject gained even more attention. The U.S.-based startup OpenAI quickly amassed millions of users throughout the globe with its ChatGPT AI-supported computer model for voice processing (Weizenbaum, 1983b). According to (von Garrel & Mayer, 2023), there are countless potential applications for speech-based artificial intelligence systems like ChatGPT. For example, according to (Berdejo-Espinola & Amano, 2023), these technologies can be used in a scientific setting to assist with text analysis, translate texts, or generate research abstracts. Along with that, there are already publications that list these kinds of tools as co-authors (Stokel-Walker, 2023). Tools like these could be useful in the classroom for a variety of purposes, including helping students reflect on scientific processes, proofreading and optimising texts, and preparing for exams. On the other hand, there are a number of dangers associated with this type of AI, including security issues, disinformation, and a lack of scientific rigour, among others. ChatGPT, for instance, has been acknowledged by OpenAI to occasionally produce responses that sound reasonable but are actually inaccurate and erroneous. Further concerns include the following: the use of chatbots to gather usage data, the difficulty in evaluating the results, the lack of clarity regarding authorship, and the potential for chatbots to be used without reflection or for abusive purposes. Given this background, there are already preliminary empirical studies that examine the application of AI-based technologies in different settings (von Garrel & Mayer, 2023b). Unfortunately, research on students' use of AI systems is lacking, particularly in the realms of education and research. The purpose of this study is, thus, to examine research that makes use of AI-based systems.

Scalable, customised, and data-driven learning experiences are in high demand, which is why digital education must adopt AI-based evaluation strategies (Bhutoria, 2022). It might be difficult to track students' progress in real time, pinpoint their specific areas of weakness, and provide them with timely, useful feedback when using traditional evaluation methods. By providing adaptive exams, automating grading, and providing insights that enable educators to personalise instruction to various learner needs, AI-powered evaluation systems can boost educational quality (Wang et al., 2024). With the rise of digital education, it is crucial to incorporate AI into evaluation procedures to ensure more efficient, equitable, and engaging learning results.

**Emergence of Moodle as a Preferred LMS in Education**

The last several years have seen profound changes to the working environment within the field of higher education. Innovative technology and approaches are important, but the question of their long-term viability is still important. Among the many worldwide trends highlighted in the 2021 EDUCASE Horison Report are: online faculty development, remote work and study, an ever-increasing digital barrier, hybrid study models, and a growth in the usage of teaching and learning technologies. According to (Kelly et al., 2021)There are a number of important technologies and methods that will shape the future of higher education. These include AI-powered blended and hybrid learning, educational analytics, microlearning, open educational resources, and high-quality online learning. Institutions of higher learning in Ukraine are actively participating in the creation and implementation of cutting-edge educational technology. Simultaneously, educators in Ukraine must make the most of their resources in light of the contemporary conditions. Wartime circumstances highlight the continued significance of distance learning (Semerikov et al., 2023). Asynchronous learning arrangements, in particular, are becoming increasingly popular. Maintaining a good level of education is difficulty for teachers who have restricted access to varied learning methods. Given these considerations, it is imperative that online learning platforms become hubs for education that provide opportunities for the integration of diverse pedagogical stances and practices. With the use of e-learning, a variety of resources, including multimedia, may be centrally located. In addition, the use of e-learning platforms enables us to establish the crucial elements of continuous student support, frequent feedback, and assessment. Innovative learning tools broaden students' intellectual horizons and inspire them to seek out alternate means of task completion. For that reason, the paper's writers centre their discussion on how to use an e-learning system to introduce new approaches to education.

The use of cutting-edge IT is not necessarily indicative of innovative pedagogical practices. As an alternative, innovative learning is the proactive application of novel pedagogical strategies and procedures. Blended learning, problem-based learning, project-based learning, formative assessment, gamification, storytelling, case method, collaboration, etc., are among the most effective methods (Rashevska & Kiianovska, 2023); (Trehub, 2013); (Zhorova et al., 2022); (Polat, 2023). The authors discuss some of the asynchronous learning strategies outlined above and provide instructions on how to use the e-learning platform Moodle to put them into practice, all while keeping in mind the present state of Ukrainian education.

The educational landscape has seen significant changes over the past century, and the introduction and growth of online learning methodologies have had a profound effect on these changes. While students began receiving coursework via the mail in the 19th century, due to technical advancements, the field of distant learning experienced rapid growth in the middle of the 20th century (Raouna, 2024). Thanks to computer-assisted instruction (CAI), which emerged in the '60s and '70s, students were able to actively participate in their own education. Radio and television transmissions provide the basis for multimedia remote education (Lu & Shen, 2023) that is based on this technology. A paradigm shift and greater accessibility to educational resources were brought about by the advent of internet-based learning platforms in the 1980s and 1990s, such as Bulletin Board Systems (BBS) and the World Wide Web (WWW) (Kentnor, 2015). As new methods of online education emerged to cater to students' diverse preferences in how they absorb information, many modalities emerged. The benefits of both synchronous and asynchronous learning models were highlighted by (Scheiderer, 2021). Synchronous learning enabled instructors and students to interact in real-time via online chat rooms and classrooms, while asynchronous learning allowed students to study at their own pace and access recorded lectures. An LMS is a web-based tool that aids educational institutions in managing their course content, distributing it to students, and monitoring their academic performance. Within the LMS, there is a shared space for instructors, students, and administrators to work together, access and share resources, complete activities (such as tests and assignments), and monitor progress (in terms of both time and grade). LMS have become indispensable in schools, particularly those at the university level, due to the central platform they provide for organising and delivering educational content According to (Agaci, 2017).

Prior to the COVID-19 pandemic, in-person interviews were the standard for evaluations. Everything from oral presentations to hands-on labs to written exams was a part of the program. Because the events transpired in real classrooms, instructors could monitor their pupils closely and offer helpful feedback. Standardised assessments were also commonly used to assess pupils' progress at various grade levels. Classes both with and without a STEM (Science, Technology, Engineering, and Mathematics) emphasis employed this strategy for teaching. The immediate need to transition to online classrooms necessitates a radical overhaul of their learning and assessment practices for COVID-19 (Draskovic et al., 2016). According to (Sato et al., 2024), conventional schools have reevaluated their methods of teaching and assessment in the face of online resources due to the proliferation of online learning.

LMSs have become increasingly important in contemporary education due to the fast shift towards online learning, which has been expedited by the COVID-19 pandemic (Keržič et al., 2021). According to Gamage, Ayres, and Behrend (2022) and Kumar, Gankotiya, and Dutta (2011), LMS provide strong frameworks for distributing course materials, encouraging student participation, and, most importantly, administering exams remotely (Gamage et al., 2022); (Kumar et al., 2011).

Moodle (v.4.4) is noted for its extensive features for online evaluations and its versatility, making it stand out among the many LMS systems (Huerta et al., 2022). A wide variety of question styles are available to teachers in Moodle, from the more basic Multiple-Choice and True/False formats to more complex structures like Cloze and Numerical questions (Aydin & Tirkes, 2010). By providing a range of question kinds, instructors are able to meet the needs of students with varying learning styles and assessment preferences. Moodle has a far larger user base than the next most popular LMS, according to the data given.

Rapid development of online education has occurred since the 2020 COVID-19 pandemic. Many facets of human life, including education, were impacted by the epidemic, say researchers. Before the pandemic, all school activities took place in physical classrooms; during the pandemic, they took place remotely, both online and offline; and after the pandemic, students could participate in a hybrid of these three modes of instruction known as blended learning. According to (Stoian et al., 2022), this variation was deemed beneficial for educators and learners alike. Or, put another way, post-pandemic learning paradigms, and blended learning in particular, are likely to be available. Institutions of higher education have used learning management systems (LMSs) as part of this strategy both before and after the pandemic. Since the COVID-19 epidemic reduced the availability of in-person instruction for numerous schools around the world in 2020, people have turned to learning management systems (LMSs) to continue their education (Habibi et al., 2023). According to Alexe et al. (2021), there were 561 LMSs available worldwide for educational and academic purposes on an international forum for software assessment and selection.

Recent comprehensive research on LMS usage trends found that, among open-source LMSs, Moodle was the most popular and preferred choice (Stoian et al., 2022b). Teachers should familiarise themselves with learning management systems (LMSs) like Moodle after recent studies found that they improve students' scores on educational assessments.

High-quality human resources are the key to national development, and education is the key. In Indonesia, the quality of education is still becoming a major challenge, especially in the changing times influenced by the rapid development of technology in the era of globalisation. Technology has an impact on aspects of education, as well as on other aspects of society (Al-Malah et al., 2020b). The development of technology has changed the world like never before (Wolff, 2021a). The acceptance of technology in education is a common factor that must be considered to be integrated into the educational environment (Wolff, 2021b). Technology-based learning reflects the relationship between technology and the world of education that helps shape scientific thinking and meet students' information needs (Mhlongo et al., 2023). Using technological resources as a learning medium is one method of incorporating technology into education. Learning media is an educational tool that can be used by teachers to help students learn more and change the way of learning from conventional lecture into making it more attractive and interesting. Along with the development of the times, every individual has the opportunity to utilize technology as a positive and beneficial learning tool with wise management (Parveen & Ramzan, 2024). Learning media is one of the important tools in the teaching and learning process, which can increase effectiveness and efficiency.

In order to raise the bar for student learning, it is crucial that educators seek out innovative approaches and materials. The development of successful learning technology has allowed for the creation of advanced learning methodologies, which in turn have made traditional textbooks more accessible to students and, ultimately, improved the quality of instruction. One of the greatest technological triumphs of the contemporary era, the rise of online education has greatly increased access to education by making it possible to study anywhere, at any time. The works of (Benson & Samarawickrema, 2007); (Yucel, 2006) are cited. In 2002, with the aid of the open-source intranet Moodle, a digital learning environment and a learning management system were merged to establish one of the most famous educational platforms globally. It opens the door for connecting to student information systems and authentication procedures. Moodle is an online learning management system (LMS) that may be accessible from any computer, intranet, or Internet connection (Yucel, 2006b). Furthermore, Moodle is a teaching platform that equips students with the resources they need to develop their independence. Online learning principles are defined here. (Sife et al., 2007) shows that traditional methods of instruction, such as in-person classes, work wonderfully with the Moodle platform. The administration and execution of teacher training are both handled by Moodle users.

Moodle is one of the most popular LMS which have gained widespread use over the last 20 years, both in academic and business education. Being an open-source platform, Moodle enables institutions to create and customise learning environments to meet their individual pedagogical objectives, and remains cost-effective in comparison with proprietary LMS systems. Its extensible architecture and vibrant plug-in ecosystem enable it to be used with tools to deliver content, assessments, analytics, and collaboration with ease, making it highly flexible to various teaching and learning requirements. Moodle is an open and sustainable platform, highly scalable, and innovative with a strong international community of educators and developers in the world of online learning.

In India, Moodle has been quite useful because it is flexible and accessible to institutions that intend to bridge the divide between digital infrastructures. Its low bandwidth compatibility and multilingual support qualify it to be used in the socio economic and linguistic diversity of Indian learners. Moreover, the emerging government policies, such as the National Education Policy (NEP) 2020, which encourage the usage of technology-enabled education, have made Moodle a common choice among colleges, schools, and corporate training. The fact that it is used by colleges and universities, skill-training sites, and MOOCs implies that it should be able to serve as an infrastructure to support massive online learning. This higher adoption shows how Moodle can be best regarded as a strategic tool of accessible, equitable and future-ready education in India, instead of a technology solution.

**Challenges in Traditional Evaluation Methods within LMS Platforms**

Though LMS such as Moodle have become commonplace in educational institutions, much of the assessment of student learning on these systems still involves more traditional assessment tools like quizzes, multiple-choice tests, and assignment that must be graded manually (Kasabova et al., 2023). Although these tools offer a foundation to the measurement of learning outcomes, they do not offer much depth to the assessment of student understanding especially in open-ended and higher-order tasks (del Gobbo et al., 2023). Manual scoring, particularly in big classrooms or mass open online courses (MOOCs) becomes time and resource-consuming to the teachers. In addition, human evaluation may be unreliable and subjective, which creates concerns about the accuracy and fairness of grading.

One more dramatic weakness of the traditional methods of evaluation in LMS platforms is the lack of prompt and individual feedback. Automated grading systems that are found on most LMSs are normally limited to objective question types and leave little room to evaluate on a more nuanced level or offer adaptive learning (Khatser & Khatser, 2022). Consequently, delayed, generic or minimal feedback is often provided to students which does not adequately assist them to improve (Meyer et al., 2025). This inability to assess at the individual level makes learning gaps widen and engagement levels low in contexts like India where the student-teacher ratio in a classroom can be as high as 50:1 and the learners can have varied backgrounds. This situation greatly necessitates the need to investigate more sophisticated, AI-enhanced assessment models that can overcome these shortcomings and make LMS platforms more effective in facilitating meaningful learning experience (Guo et al., 2025).

The advent and development of online learning approaches have greatly impacted the educational landscape, which has experienced substantial changes during the last hundred years. It all started in the 19th century with mail-order correspondence courses, but with the advent of new technologies in the middle of the twentieth century, distant learning took off (Casey, 2008). Multimedia distant education was pioneered by radio and television broadcasts, and computer-assisted instruction (CAI) was born with the advent of personal computers in the 1960s and 1970s (Munna et al., 2024). Several modalities occurred as online learning approaches developed to meet the needs of students with varying learning styles. According to (van den Oever & Koornneef, 2025), synchronous learning allowed for real-time engagement between teachers and students through online chat rooms and virtual classrooms, whereas asynchronous learning allowed for flexibility through self-paced study and access to pre-recorded lectures. New developments have resulted in adaptable learning platforms that provide students with unique educational opportunities. While obstacles like limited technology and lack of accessibility still exist, new technologies such as artificial intelligence (AI) and virtual reality (VR) hold great potential to make online learning more engaging.

Despite its importance, grading remains a labor-intensive process that poses significant challenges for educators. Traditional methods such as rubric-based evaluations and norm-referenced grading often fall short of ensuring consistency and objectivity, as they are prone to subjectivity and repetition (Munna et al., 2024). Manual assessment methods also struggle to provide timely, personalized feedback at scale, which is a critical component of effective learning (Ling, 2024). These limitations hinder both the efficiency and effectiveness of assessments, particularly in large classes or massive open online courses (MOOCs), where prompt and reliable feedback is essential to student engagement and performance.

**Introduction to Large Language Models (LLMs)**

One area of artificial intelligence that studies how computers and humans communicate through language is known as “Natural Language Processing” (NLP) (Khurana et al., 2023). Most notably, NLP models may teach computers to read, comprehend, and even mimic human speech and writing. Scaling up model size, pretraining corpus, and computational resources allows for the creation of “Large Language Models” (LLMs), which are advanced NLP models belonging to the PLM category (Qin et al., 2025). To put it succinctly, LLMs are taught using transformer models, which are a specific kind of deep learning. They are models of neural networks that learn contextual linkages in the input sequences through multi-head attention and self-attention, which allow the model to see the complete context rather than constrained to fixed-size windows. According to (Kang et al., 2024), this approach does not require recurrent and convolution layers. Other important elements in the transformer architecture are the encoder and decoder units that process the input sequence to generate the output sequence (E. Y. Zhang et al., 2023). However, a transformer's structure might vary depending on its function and design. Transformers can be designed with either an encoder structure or a decoder structure. An encoder and a decoder module are required, for instance, for a task like language translation that requires both an input sequence and an output sequence. However, an encoder is the sole tool that may be used for language modelling or text classification. To learn about non-linear interactions in the data, feedforward neural networks are another crucial part of a transformer design. Positional encodings, on the other hand, give information on where tokens are in the sequence (Baniata & Kang, 2024). Learning contextual information through the use of massive databases enables LLMs to comprehend intricate linguistic structures and subtleties, which is their most distinguishing feature. As a result, LLM applications are widely used in various fields like as sentiment analysis, chatbots and virtual support, language production and translation, speech recognition, text comprehension, and more.

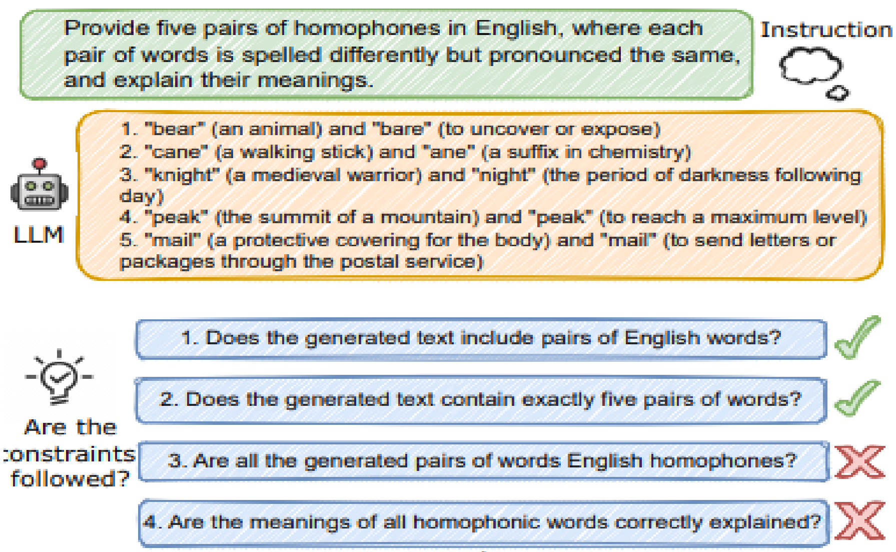


***Figure 1***
***An example from Info Bench of how an LLM fails to follow the complex constraints in the instruction.***

***Note. Reprinted from Sun et al. (2024)***

LLMs have achieved impressive performance across a wide range of NLP tasks. Instruction tuning, also known as “supervised fine-tuning: (SFT) (Ouyang et al., 2022a), has enabled LLMs to better align with human preferences by following human instructions and generating helpful, honest, and harmless(Ouyang et al., 2022b) responses. Improving instruction-following abilities is a core direction of concern for the LLM community. Recent progress in the field has enabled opensource LLMs to demonstrate impressive performance in following instructions across numerous tasks. Nonetheless, LLMs, particularly those that are open source, still often struggle with more challenging tasks that include complex constraints in the instructions. Figure 1 presents an instance illustrating an open source LLM's failure to adhere to instructions with multiple constraints. However, the challenge of enhancing LLMs to follow complex constraints is an area that remains insufficiently explored.

Systematic reviews (SRs) play a vital role in evidence-based medicine, but they are notoriously labour- and resource-intensive. Early studies stressed their high resource demands and the need for multiple reviewers (Mulrow, 1994; Marchevsky & Wick, 2015), while recent research confirms that these challenges persist even with modern AI-assisted methods (Nussbaumer-Streit et al., 2023; Cierco Jimenez et al., 2022). This evolution highlights how technological tools may reduce some effort, but the fundamental complexity of SRs remains. There has been a proliferation of AI tools in recent times. For task-specific choices, traditional ML uses supervised or unsupervised methods. Bidirectional Encoder Representations from Transformers (BERT) and other transformers significantly enhanced the understanding of contextual and semantic language. No task-specific training is necessary for generative LLMs like Claude, "Generative Pretrained Transformer" (GPT) (Igarashi & Suryadarma, 2023), or LLM Meta AI. These are constructed using transformers that only use decoders and have been trained using massive amounts of textual data. However, there are dangers, such as destructive replies or false information, associated with its obtuse architecture. The medical field (Lee et al., 2023) and the field of health research (Lund et al., 2023) are currently conducting significant testing of LLMs.

**Leveraging Large Language Models (LLMs) for AI-Powered Educational Assessment**

The widespread use of AI in classrooms is changing the way students learn and teachers approach their jobs. Automated grading tools and clever tutoring systems (Tan et al., 2025), With the help of AI, educational opportunities are becoming more interactive, streamlined, and tailored to each student. Personalised feedback, direct assistance, and heightened interest are just a few ways in which these systems cater to the unique requirements of each learner (Kabudi et al., 2021). Meanwhile, AI relieves administrative processes, including scheduling and grading, so that educators can concentrate on the pedagogical objectives (Luckin et al., 2022). The possibilities of AI to revolutionise learning are enormous, but there are also issues of data privacy, algorithmic bias, and ethical AI applications in education (Akgun & Greenhow, 2022). The introduction of AI in education is not only improving the delivery of instructions, but also reshaping the pedagogic models, the curricular design and the roles of educators. Education using AI is moving towards more student-centred, interdisciplinary and personalised models of education. The role of teachers in the classroom is shifting towards the facilitator of self-directed learning processes and a promoter of metacognition and reasoning ethically (Karataş & Arpaci, 2021a). Moreover, educational theories like AI-TEACH and dual-contrast models are coming on the scene to promote analogical thinking, systems thinking, and ethical sensitivity in AI-based classrooms.

NLP and AI have played a significant role in the development of question-answering systems. Rules-based and retrieval-based QA systems have been used in a variety of areas still lacking the capability of understanding complex questions, and providing contextually accurate answers (Karataş & Arpaci, 2021b). With the advent of LLMs like GPT, BERT, and T5, question-answering systems have undergone a paradigm shift, making it possible to provide more accurate, coherent, and human-like answers. These developments have driven research and innovation in AI-powered QA applications in various industries like education, healthcare, customer service, and business intelligence (Rashid & Kausik, 2024). LLMs apply deep learning methods, specifically transformer architectures, to process and produce human-like answers to natural language questions (Raiaan et al., 2024). In contrast to traditional methods based on pre-designed templates or keyword matching, LLMs use extensive amounts of training data to learn semantics, context, and intent. This allows them to process various question formats, unclear questions, and domain knowledge with high accuracy. Therefore, QA systems based on LLMs are being incorporated into virtual assistants, chatbots, search engines, and enterprise software to augment user experience and automate information fetching. Even though they have several benefits, it is challenging to implement LLM-based QA systems. Computational cost, response time, and requirement of enormous computational resources are some of the serious issues(Mishra & Jain, 2016). Furthermore, bias, hallucination (creation of false but plausible-sounding information), and ethical aspects also need to be addressed so that reliable and unbiased AI-driven answers can be guaranteed. Researchers and developers continue to seek a way to optimise performance, such as fine-tuning, prompt engineering, and model compression, without sacrificing accuracy and efficiency. The other key aspect of AI-based QA systems is the versatility to other domains and other languages.

The present fast development of AI, especially LLMs, has proven to have great potential in automating tasks and provides a vast amount of opportunities in making teaching and learning experiences more enjoyable. The same LMs are now facilitating the teacher-led learning, the AI helps aid the human teacher by relieving them of the repetitive tasks and they can focus more on the interactive and creative areas of teaching (Kammoun et al., 2022). These models open doors to context-sensitive resources that are rich in content and can be used by both educators and learners to overcome language barriers and reinvent the classroom experience. Additionally, they can support new forms of teaching and learning and enable a higher level of critical thinking in a wide range of learning contexts due to their ability to take advantage of modern cognitive intelligence.

LLMs are a category of language models that have demonstrated exceptional capabilities in various NLP tasks (Khan et al., 2022). They have transformed the natural language understanding and generation by being able to have a deep understanding of language, humanlike text generation capabilities, complete problem solving capabilities and contextual awareness (Yao et al., 2024). They have the ability to address text questions even though they have not been explicitly trained on the task in question (Ravi et al., 2023). This makes it invaluable in various applications. Thus, LLM research has become highly sought-after. Also, innovations in education technology that use LLMs have shown the potential to automate several educational tasks (Yan et al., 2024). Being able to code is seen as a valuable skill that is in high demand across different industries. Programming is employed in fields like Data analysis using programming languages like Python or R and software development using programs like C++, JavaScript, and Golang. Nevertheless, the focus has been on the scarcity of programming teachers, creating difficulties for individualised learning in classrooms, and causing frustration among students (Feng et al., 2023). Independent learning is achievable with determination. However, the learning process often requires assistance, especially in programming, which many students find abstract and challenging due to their unfamiliarity with programming languages. Recently, LLMs have started to play a significant role in computer programming and education.

**Aligning AI Integration with Pedagogical and Learning Objectives**

Reasoning, learning, and decision-making are all examples of activities that have long been associated with human intellect, and AI is quickly revolutionising these fields by making them more efficient and precise (Rashid & Kausik, 2024). In Thailand, the National Higher Education Qualifications Framework (Thai Qualifications Framework for Higher Education, TQF) is employed to serve as a context to inform the process of curriculum development. The TQF defines the system of qualification in the country regarding the stages of qualification/levels, standards of learning outcome and the characteristics of curriculum at each level. It focuses on life-long learning and on matching educational experiences to particular requirements of students, encouraging life-long learning and making sure graduates achieve the required standards of quality (Thanaphakawatkul et al., 2023).

Its teaching and learning role is shifting due to the fact that it is offering individual student experiences depending on their student needs through adaptive learning systems, intelligent tutoring and automated grading. NLP allows a dual-party dialogue, and Chabot and virtual assistants can offer help on-demand. Data analytics and predictive modelling enable teachers to identify patterns of students and take precautionary measures, and augmented and virtual reality technologies offer immersive learning. The ability of AI to simulate human cognitive processes using machines, especially computers, is rendering AI applications very useful in more and more industries today (Ali, 2020). AI is also useful for curating and creating content, which helps both students and educators find what they need. Improving learning outcomes, optimising teaching techniques, and creating a more inclusive and engaging educational experience are all possible with the integration of AI into education, which is set to continue evolving. AI is a system that can analyse human speech, understand human speech, boost student productivity and competency, and implement the flipped learning method to language training. Among the hallmarks of the flipped classroom model are a student-centred culture, a high degree of autonomy for individual students, and thoughtful selection of course materials (B. Li & Peng, 2022). There is growing speculation that traditional academics, who primarily focus on imparting knowledge, will be replaced by AI due to the rapid advancements in AI (Pila, 2023).

As a means of keeping pace with the evolving needs of the students of the contemporary era, it is presently necessary that educational establishments integrate the latest technological devices. As the digital, biological, and physical worlds are converging with the advent of the fourth industrial revolution, the education system is going through an extraordinary transformation period (Zou et al., 2025). New forms of learning and the emerging Education 5.0 is at the forefront of this revolutionary change, bringing in personalised and adaptable learning experiences through the central role of AI in the classroom. It is possible to concisely trace the evolution of education via its several phases. Education 1.0 was characterised by a traditional, one-size-fits-all method, where the focus was on the teacher and the students were expected to memorise facts and figures. It was with the introduction of education 2.0 that the students were in a position to contribute towards their education by utilising technology and multimedia in the classroom environment. Education 3.0 provided the foundation of the current era of education with the focus on student-centred learning, collaborative learning, and the use of web-based resources (Songkram et al., 2019).

### 1.2 Research Problem

Despite the extensive use of Learning Management Systems (LMS) like Moodle in learning institutions, conventional assessment systems in these systems are always limited and are becoming less relevant in the contemporary learning process that is increasingly fast-paced. The most notable weakness is the absence of individualization since the conventional assessment practice generally assumes one-size-fits-all model that does not consider the learning styles, paces, and preferences of individual students. Such rigidity may result in a lack of student engagement, motivation, and less than ideal learning performance. Also, conventional evaluation techniques tend to be manpower intensive especially in the assessment of open-ended or subjective answers. The heavy grading burden placed on teachers limits the time and resources teachers have to spend on other important tasks in instruction, such as offering personalized assistance, improving curriculum, or introducing new teaching methods.

The expansion of the traditional assessment systems is also unscaled, since online education is constantly growing, the manual system of grading cannot effectively grade the rising number of students, which delays feedback on students and negatively affects timely learning intervention. Moreover, these conventional methods make it difficult to identify students that might need some extra assistance at an early stage. The deficient nature of hard and statistically based indicators restricts timely action to be taken by educators and this leads to increased dropout rates and late academic support. Together, these deficiencies reveal the incumbency of more adaptive, efficient, and context-conditioned assessment solutions that can be used to answer the pedagogical and infrastructural challenges of contemporary digital education, especially in the diverse and rapidly changing Indian EdTech landscape.

### 1.3 Purpose of Research

The overarching aim of the study is to explore the opportunities of incorporating AI-driven Large Language Models (LLMs) into the Moodle Learning Management System (LMS) to improve the process of student assessment in the Indian EdTech environment. In particular, the research aims at addressing the question of how evaluation with the help of LLM can enhance the efficiency of grading, give personal feedback, and aid adaptive learning, thus, enhancing the overall effectiveness and quality of online learning. The research will help produce actionable information regarding how AI can help solve the drawbacks of current approaches to assessment labor-intensive grading, a lack of personalization, limited scalability, and timely detection of at-risk learners, by exploring the perceptions of stakeholders, practical issues, and implementation viability of the concept of LLM applications.

Integration of LLM into Moodle is expected to revolutionize the assessment context by using the large data of learning materials and student interactions of the platform to provide teachers with real-time, contextualized information. This AI-driven grading can be used to assess complex student answers, minimize grader bias, and provide extremely trustworthy and objective feedback, and at the same time, provide personalized learning suggestions in relation to the student-specific needs. In addition to that, early identification of learning difficulties can be supported by LLMs, making it possible to initiate timely interventions to enhance student retention and academic outcomes. Encroaching the adaptive and data-driven assessment through centralization in an environment that is familiar with LMS, this study aims to prove the ability of LLMs to make a more efficient, equitable, and learner-centered education option in India, making a statement in both theory and practice to EdTech.

## 1.4 Significance of the Study

The research is of critical importance because it investigates the life-altering possibilities of applying AI-based assessment, namely, LLMs, to the Moodle learning management platform in the Indian EdTech industry. Digital education is growing at a very fast pace in India, and the country requires scalable, accurate, and personalised assessment solutions. By exploring how LLM-based assessment can affect teaching efficiency, the performance of students, and individualisation of learning, the research will allow actors in the sphere of education, EdTech developers, and policymakers to gain practical solutions. The results may be used to inform the design of future digital learning infrastructure by encouraging AI-supported assessment practice to overcome the shortcomings of conventional assessment practices, increase student retention, and improve overall learning performance in dynamic multi-cultural learning settings.

## 1.5 Research Purpose and Questions

This study aims to discuss the use of AI-based assessment tools, especially those based on LLMs, in the Moodle LMS to support online learning in the Indian EdTech industry. The research will consider the ways in which LLMs can enhance the accuracy of assessment, individualise learning, make it more efficient, and facilitate early intervention using predictive analytics. The project will compare the practical implications, advantages, and limitations of introducing such AI-based assessment systems to understand what impacts could be more effective and scalable in the context of digital education in India.

- How effective are existing AI-based Large Language Models (LLMs) in evaluating student performance on Moodle in the Indian EdTech context?
- What are the current AI tools and technologies used in Moodle for automated evaluation, and how do they address the unique needs of the Indian education system?
- In what ways can the integration of LLMs into Moodle be optimised to improve teaching methodologies and personalised evaluation in Indian classrooms?

# Chapter II:
# Review of Literature

## 2.1 Theoretical Framework

The proposed research is based on "Technology Acceptance Model" (TAM) and the "Constructivist Learning Theory" (CLT) to investigate the delivery of LLM-based assessment tools in the Moodle platform in the Indian EdTech environment. Davis (1989) proposed TAM, which can be used to explain how teachers and students view and implement new technologies (Legramante et al., 2023). These core constructs of the model, "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEOU) assist in assessing whether the users believe that the AI-powered evaluation is useful and efficient and can be adapted to personal needs, and whether the user interface is simple to use and understand (Niu & Mvondo, 2025). These aspects shape user attitudes and behavioural intentions in the adoption of AI in educational evaluation.

Simultaneously, CLT justifies the teaching logic of implementing LLMs into learning systems (Lopez-Gazpio, 2025). In LT, there is a focus on how learners construct knowledge through reflection, interaction and through individual engagement. The use of LM-based assessment tools can augment this constructivist approach by offering feedback on a real-time basis, identifying knowledge gaps, and adjusting to individual learning styles (du Plooy et al., 2024). This more individual, feedback-based context is better suited to deeper learning, more student agency, and earlier interventions, which are all relevant to the goal of better educational outcomes through the use of AI in teaching.

### Technology Acceptance Model (TAM)

Davis's (1989) TAM is a foundational model for how users adopt and make use of new technologies (Ma & Liu, 2005). It relies on two constructs: PU, the belief that a system would improve performance, and PEOU, the belief that the system would require no effort from the user. In relation to the evaluation of the use of LLM-based tools in Moodle, TAM is also used to understand how teachers, students, and administrators develop their attitudes toward these technologies as useful and easy to use (Neumann et al., 2025). The positive impressions in both spheres are likely to enhance acceptance, intention and long-term engagement in teaching and learning activities.

The rate of digital literacy and access to technology in India, in turn, can differ significantly in relation to the EdTech services market, and, accordingly, the applicability of TAM gains even greater significance. Teachers can be demotivated to use the LLC-based assessment system because it is perceived as a complex or unreliable system, regardless of its capabilities (Holden & Rada, 2011). Conversely, in the event users learn that the system will allow them to grade more accurately, be less labour-intensive, and provide them with timely feedback, in addition to being easy to use, they will be less inclined not to trust it, and use it in their teaching. Thus, TAM is an effective tool in this research to identify the factors that regulate the acceptance of AI-based assessment by users and its feasibility to be implemented by a large number of users of Moodle.

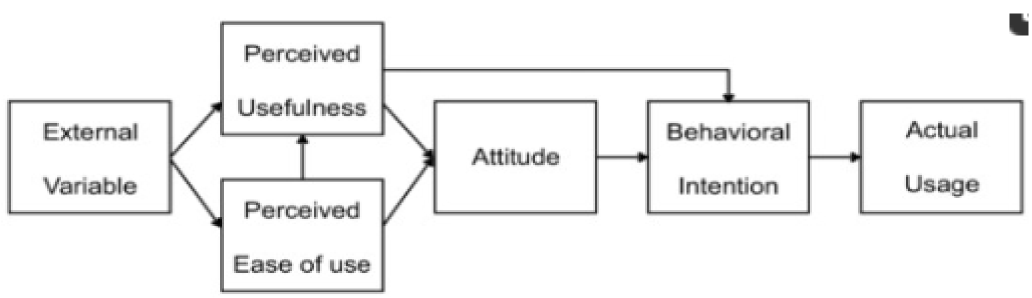


***Figure 2***
***Technology Acceptance Model (TAM) by Davis (1989)***

***Note. Adapted from Park & Park (2020).***

### Constructivist Learning Theory (CLT) with AI Augmentation

"Constructivist Learning Theory" (CLT) is founded on the concepts of Piaget (1972), Vygotsky (1978) who underline that learners develop knowledge through the processes of experience, reflection, and communication with the environment. In this context, learning is portrayed as a person-cantered and transformative process which is conditioned by the background and context of the person who learns and how they interact with it (Chand, 2024). When the CLT is used in digital education, one can state that it promotes student independence, group cooperation and continuous feedback, which is a major contributor to the formation of deeper comprehension and critical thinking. This theory can be used as a guideline in Moodle as the development of AI-based learning environment is no longer a one-size-fits-all solution.

To enhance the CLT, "Large Language Models" (LLM) are also introduced to provide real-time correction of the learner, and intelligent feedback. LM can assess student contributions and diagnose every student individually to facilitate individualised feedback to facilitate the constructivist goal of personalised and meaningful learning (Garcia et al., 2024). Additionally, such functionalities as the ability to predict early dropout and monitor progress allow educators to deliver timely support and ensure learners stay motivated. Such AI augmentation allows students to take control of the learning process and provides educators with data-driven tools to support them in the process of learning, thereby staying true to constructivism in a technologically enhanced environment. Furthermore, the integration of AI-powered learning analytics ensures that learning pathways can be dynamically adjusted in response to student needs, thus promoting adaptability and lifelong learning skills. By blending CLT with AI augmentation, digital platforms like Moodle are positioned not only to replicate classroom practices but to expand them, offering learners more agency, creativity, and opportunities for critical engagement.

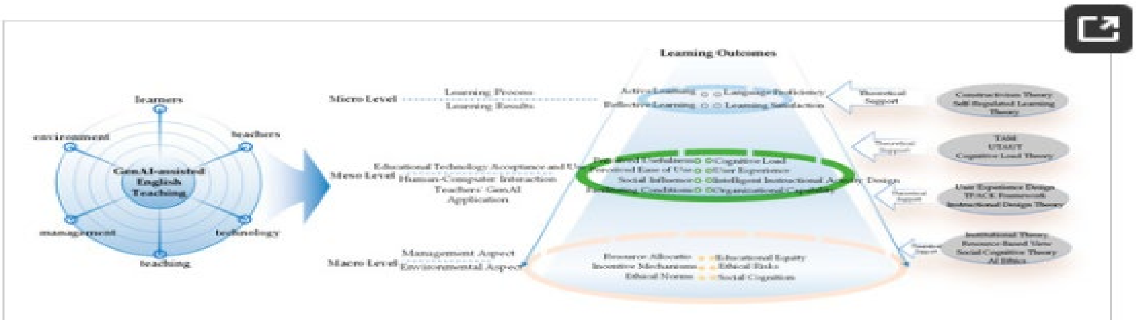


***Figure 3***
***Multidimensional influence mechanism analysis framework for GenAI-assisted English teaching***

***Note. Reprinted from Zhang & Dong (2024).***

### 2.2 Overview of Artificial Intelligence (AI) in Education

With its innovative approaches to learning, administration, and instruction, AI has been a game-changer in the field of education. Intelligent tutoring systems powered by AI, automated grading, adaptive learning platforms, and predictive analytics are revolutionising the way students and teachers interact and engage with course material. The recent developments of LLMs have also broadened the range of AI applications in education to provide the more detailed, situation-specific feedback and evaluation. Educational establishments are becoming more digital, with some educational institutions adopting tools like Moodle. The use of AI-based tools is a consideration not only to automate it, but also to personalise learning, as well as enhance the accuracy of assessment, and inform data-based decisions. This expanding body of research demonstrates how AI can be used strategically to enhance learning and improve operational performance in varied learning environments.

(Vieriu & Petrea, 2025) Bringing AI into the classroom has both facilitated and hindered students' learning. This study investigates how AI influences students' perspectives on and experiences with AI adoption, as well as their intelligence, knowledge acquisition, and academic achievement. Undergraduates from Romania's National University of Science and Technology POLITEHNICA Bucharest took part in the research since they had firsthand exposure to AI-powered lectures. A total of 85 individuals were selected for this study's representative sample using purposive sampling. Seven of the eleven questions were closed-ended and assessed the use, efficacy, and perception of AI technologies; four of the eleven questions were open-ended and enquired about experiences, expectations, and anxieties. The data was collected using an eleven-item structured questionnaire. For quantitative data, they utilised frequency and percentage calculations; for qualitative responses, they employed a theme analysis. To get the most complete picture of the themes, this research used both vertical (based on respondents' answers) and horizontal (comparing datasets) themes. Evidence suggests that AI has the potential to bring about far-reaching changes, such as increased student engagement, better academic performance, and personalised lessons. The decrease in critical thinking abilities, academic dishonesty, data privacy concerns, academic over-reliance on AI, and other interpersonal issues were also raised. The study highlights the importance of having a suitable system of AI integration driven by ethical principles in order to maximise advantages and reduce dangers. Finally, AI has the potential to improve learning and academic achievement. However, there are still concerns with accuracy, cognitive disengagement, and ethics that need to be addressed before AI can be used in the classroom effectively. A neutral stance is necessary to guarantee ethical, efficient, and equitable learning in educational contexts that employ AI.

In this study, (Döğer & Göçen, 2025) explore The research explains how K-12 teachers in 15 eTwinning countries view and incorporate AI tools in classrooms and identifies opportunities as well as difficulties. They employed a qualitative case-study design with semi-structured interviews in a combination of criterion and maximum-variation sampling to encompass a diversity of country settings. According to the respondents, AI streamlines lesson planning, assessment, and content development, helps to plan projects and work in multicultural teams; and helps to develop skills of the 21st century (the 4Cs). However, they also raised sociological and ethical concerns of privacy, bias, overdependency, AI-driven capitalism, and digital divides that are still common in K-12 schools. their results will provide best-practice information to early adopters and a guide to wider professional growth and teaching architecture over the next decades. The main implications are the design of leveled training courses, creation of transparent ethical principles, explainable AI innovations and infrastructural investments to fill the gap that has always existed.

## 2.3 Educational Applications of Large Language Models (LLMs)

(Ruf & Detyniecki, 2024) give an easy approach to incorporating LLMs into classroom instruction. Their approach is focused on enhancing personal understanding through the incorporation of a unique component into internet videos. Together, the advantages of rephrased and elaborated explanations common in face-to-face contacts and the low threshold for involvement in digital encounters help to close knowledge gaps on a large scale. They built a prototype and ran a proof-of-concept experiment to show that their method is technically feasible; you can test it out on their website. Their use case also demonstrates how LLM-powered applications can employ caching to lessen their impact on the environment.

(Minh et al., 2025) Since the publication of ChatGPT in 2022, several LLMs have shown remarkable progress in different "Natural Language Processing" (NLP) tasks. These include GPT4, Gemini 1.5, Claude 3.5 Sonnet, and Llama3. Although LLMs have been successful, they are still computationally expensive to fine-tune and deploy, particularly in settings with limited resources. As part of their research, they developed VietEduFrame, a system for managing educational institutions in Vietnam using LLMs. One of their most important contributions is a customised dataset that takes into account the specific difficulties encountered by educational systems operating with constrained budgets. This data is founded on the learning papers of students at Hanoi VNU. Their method has been shown by large amounts of experimental evidence to be more efficient and accurate than existing methods, and offers a viable alternative that will allow superior management of education where resources are limited. They discuss potential constraints in terms of the size of the application and the strength of subsequent applications, although their model is based on synthetic data to augment real data.

(X. Zhang et al., 2024) The potential implication of the introduction of LLMs in higher education teaching was discussed in this research. It also discusses how LLMs could be used to support personalised learning, improve interaction between teachers and students, and foster content innovation. The study also briefly discusses issues associated with the use of LLMs, including the re-evaluation of the role of the teacher, data privacy concerns, and technical difficulties of dealing with higher cognition. A literature review, survey, and case study analysis were all part of the mixed-method approach employed in the study. In order to collect quantifiable data on the experiences of 120 professors and 533 students from five institutions in China about AI applications in education, a literature analysis was carried out. The efficacy of LLM-supported learning platforms in raising student participation, teacher-student communication, and course completion was also evaluated through the examination of case studies. In terms of personalised learning and increased classroom engagement, 68% of instructors and 74% of students said LLMs were helpful. Nevertheless, nearly 60% of educators voiced worries about students' growing dependence on AI and its potential impact on their autonomy in the classroom, and nearly half of all students were concerned about the security of their personal information. In contrast, case studies showed that student engagement increased by 25% and teacher-student interaction by 30%, although LLMs struggled with high-order thinking tasks in mathematical and other highly specialised subjects. The research finds that higher education institutions should proceed cautiously while implementing LLMs, despite their promising future in improving personalised learning and the interaction process. Equally important are teacher preparation, ethical issues, and data protection. Future research could focus on how to tailor LLMs to certain fields of study or how to combine them with emerging technologies like VR and AR to provide more interactive lessons.

(Fan et al., 2023) This study investigates the potential of LLMs to devise code-tracing questions for the purpose of teaching basic computer programming concepts. In order to train GPT4 to ask code-tracing questions based on descriptions and code snippets, they created custom prompts for it. In order to evaluate the quality of questions asked by human experts, they came up with a list of human-evaluation indicators, to compare them with the quality of the questions asked by the model. Depending on the outcomes of this study, it may be observed to which extent the LLMs may produce various forms of code-tracing questions. Their individualised tracing questions developed by humans and LLMs, could help the education and NLP research community. In this post, the possible applications of LLMs in the classroom are also discussed.

(Leiker et al., 2023) There are pros and cons of using LLMs and other forms of generative AI in the classroom, yet these technologies are quickly permeating many parts of people's lives. This study presents research on how LLMs might be used to create asynchronous courses, with a focus on adult education, training, and skill development. They used a well-established human-in-the-loop approach to determine the generated material's quality and relevance, and they built a course prototype utilising an LLM. Their research is on the possibility of LLMs to independently produce high-quality resources for adult learning. Positive new findings in educational generative AI include early indications that this method can aid in the creation of material more rapidly without sacrificing clarity or accuracy. Despite this, the study emphasises the power of LLMs to revolutionise education and urges for more investigation into their strategic and ethical applications in learning design.

(Parker et al., 2025) The purpose of this study is to determine whether the LLMs GPT-4 and GPT-3.5 can be useful tools for analysing surveys that ask students about their school experiences. Feedback analysis in the field of education has received comparatively less attention than its application in teaching and learning situations when it comes to LLM in the classroom. As a time-consuming manual analysis of textual responses may be required for survey analysis to be used in education with the goal of detecting gaps in curricula or evaluating teachers. If these goals cannot be satisfied by fine-tuning or specialised machine learning models, LLMs may offer a more adaptable alternative. They demonstrate a versatile approach to accomplishing these objectives by decomposing them into sequences of NLP activities carried out by LLM, including as extraction, theme analysis, sentiment analysis, multi-label, multi-class, and binary classification. The processes are tested using a real-world dataset that includes 2500 comments from final exams in biomedical science courses. On all tasks, they evaluate a zero-shot technique that doesn't require examples or labelled training data. This is reflective of the fact that tagged data is often absent in educational contexts. With GPT-4, they can achieve performance comparable to that of humans in numerous tasks by applying effective prompting strategies, which facilitate the mechanisms required to achieve common objectives. Moreover, they demonstrate how the analysis of chain-of-thought (CoT) reasoning by LLMs can be a valuable source of information to build confidence in practical use. Moreover, this study describes how a flexible system of categorisation criteria has been developed and can be easily customised and applicable across a broad range of online courses, courses that combine online with real-life, and those delivered face-to-face. There are indications that survey data can help identify valuable information using LLMs.

(Maity et al., 2024) During this age of generative AI, the unification of LLMs creates new opportunities in the evolution of modern education. In the framework of assessment and instruction, they aimed to discover the potential of prompted LLMs. They demonstrate the practicality of using a multi-stage prompting model driven by chain-of-thought to create language-independent multiple-choice questions (MCQs), and of using prompt-based models to create open-ended questions on technical textbooks taught in undergraduate courses with a set of designed research questions. They also consider the capacity of prompted LLMs to aid language learning in a case study of the under-resourced Indian language, Bengali, which attempts to explain grammatical errors in Bengali. They go even further, thinking about how prompted LLMs may be used to review transcripts of verbal interviews conducted by personnel resources (HR). To better understand the potential and constraints of LLMs in revolutionising educational procedures, it is necessary to compare their capabilities to those of human specialists across a variety of educational activities and subjects.

(Chen et al., 2024) LLMs hold great promise for the future of artificially generated intelligence (AGI) and have been a significant advancement in NLP. Despite LLMs' success in the broader area, they have struggled in education, where students require more specialised knowledge, customised lessons, and clear explanations of complicated ideas. This study proposes Wisdom Bot, a new LLM for education that brings together educational theories and the power of LLMs to solve these problems by making their integration into educational environments effortless. To be more precise, they train on concepts and instructions for self-instructed knowledge using Bloom's Taxonomy. supplement the model's local knowledge base retrieval and search engine retrieval during inference to make it more accurate and professional when answering factual enquiries. By using their method to various Chinese LLMs, they demonstrate its efficacy; the outcomes indicate that the improved models are capable of generating more trustworthy and knowledgeable responses.

## 2.4 The Role of Moodle in Digital Learning

(Alrikabi et al., 2022) The world is changing at a quick and complicated pace, and with that comes increased demands on the school system. In order to stay up with these changes, it is now essential to revamp and enhance the existing system for online learning. Higher education and online learning communities are rapidly embracing e-learning as integral parts of many curricula. This is particularly true in light of the rapid advancements in technology that have been made in recent decades, a factor that the Corona pandemic significantly accelerated. Since the COVID-19 pandemic impacted every corner of the globe, access to education is no longer contingent on geographical location or time zone. In this study, an open-source e-learning platform is built using Moodle. The platform offers features that help with teaching, as well as administrative duties and effectiveness linked to education. It serves both students and teachers. Also, it's crucial to understand its impact on digital skills, which have recently emerged as a top priority in the Internet realm.

(Halil et al., 2023) Moodle is an excellent platform to make online courses, training, and education available online. It also promotes valuable eLearning content distribution standards including SCORM. The aim of this study is, first of all, the construction of online learning environment (OLE) with Moodle in SMPN 4 Kolaka Utara. Second, it will develop an e-learning material package based on MOODLE which complies with the SCORM standard. Lastly, it will critically assess how the e-learning space can be constructed using Moodle. This study has led to a pioneering E-learning system known as mesikolah.com that is available on the Internet at the following address: https://mesikolah.com/. It was created based on the ADDIE model, which is an abbreviation of Analysis, Design, Development, Implementation and Evaluation. These courses are designed to meet the rigorous standards set by SCORM, which include being accessible, adaptable, affordable, durable, interoperable, and reusable. Positive user feedback, including an astounding 80% satisfaction rate on the e-Learning platform, is revealed in the summative evaluation, while the results of the formative evaluation show a good alignment with the chosen research approach, ADDIE. Additional research, such as classroom action research, is necessary, even though this study primarily concentrates on the e-Learning development stage and the preparation of content packages. The existing content bundle mostly consists of text and flash presentations, which calls for the creation of other media formats like streaming video or video on demand in the future.

(Viteri Rade et al., 2021) Both instructors and students have been impacted by the shift from traditional classroom instruction to online learning. Many people who aren't comfortable with technology have doubts about the usefulness of online courses and have stopped trying because of it. Nearly nineteen years after its creation, Moodle continues to be one of the most popular platforms for teaching and learning across educational, institutional, and corporate levels. Its user-friendly interface, security and privacy features, ease of connectivity, and access to external resources contribute to this popularity. To better understand the Moodle platform and its features as a learning environment for university students, a descriptive research study was conducted. The study included an analysis of the software tools for virtual teaching and evaluation, as well as the platform's freedoms and limitations. A documentary review served as the basis for the study. According to the research, educators can include more innovative activities into their practice when they have technical understanding of Moodle pedagogical tools and instructional design methodologies that are based on constructivism, collaborative learning, and active learning. By maximising the potential of the Moodle platform for online instruction, these pursuits enrich the educational experience of students.

This service activity, (Asmiyunda et al., 2023), aims to increase Instructor expertise and originality in relation to digital classroom management advances utilising the Moodle-based learning management system. Presentations, demonstrations, practices, and debates were the means of instruction, mentoring, and assessment that comprised this community service. They were SMAN 11 Muaro Jambi, a service partner. A questionnaire was used to gather data, which was then analysed using both descriptive and qualitative methods. Based on the average user response from the questionnaires distributed and the results of this service's digital learning media platform, which was a Moodle-based LMS, training activities were deemed very good and helpful for increasing teacher competence and creativity.

The research made by (Sylvestre et al., 2024) Some say that a nation's educational system is the best in the world. National goals are generally defined by their educational institutions. The purpose of this study was to examine how utilising Moodle and other forms of technology in the classroom affects students' and teachers' views on how to acquire the necessary level of intelligence for the workplace. The study analysed qualitative perspectives collected from a sample of university professors and students using the thematic approach; it was qualitative research. According to the findings, Moodle can help both teachers and students develop positive attitudes towards technology. Research also shows that in order to help underdeveloped nations' educational institutions; university faculty and students need to put in a lot of work to learn new technology abilities. When implemented correctly, Moodle and other LMSs have the potential to improve learning and teaching environments, which in turn can help students and teachers acquire the skills necessary to be successful in the workforce. Moodle was suggested as a tool for both students and teachers, and the study urged researchers to keep looking for ways to inspire everyone involved.

### 2.5 Traditional Evaluation Practices and Current Assessment Tools in Moodle

This study (Huerta-Gomez-Merodio & Requena-Garcia-Cruz, 2024) takes a look at how Moodle, a well-known LMS, has enabled improvements in online assessment methods. The study explores the many question types available in Moodle in light of the revolutionary effects of the Fast Test Plug In (FTP) on instructors' assessment practices prior to, during, and after the COVID-19 pandemic. This study looks at the efficacy of various question types and imports formats for extensive question elaboration. Prior to and subsequent to the development of FTP training courses, educators were polled. The purpose of this research is to compare patterns before and after the introduction of FTP in order to provide light on how teachers in different disciplines and universities have modified their evaluation processes in reaction to technological advancements. With the addition of FTP, creating and integrating questions within Moodle has become much easier. Evaluation methods in STEM and non-STEM fields are also distinguished by the study. The usage of all question categories has grown following the FTP training course, according to surveys. This includes 35% for Matching, 39% for Missing Word, and 22% for Cloze. A thorough review of recent developments in learning management systems (LMS) and Moodle's place in the field of educational technology is presented in this book.

Highlighting the influence of technology developments like FTP on assessment methods, it seeks to provide practical advice for bettering online tests.

The study (Arredondo et al., 2025) include student surveys. Context: As the semester progresses, students in an electric circuits class build upon what they have learnt. Failing to maintain a consistent study-homework regimen increases the likelihood of test failure and makes it more difficult for students to make the most of their class time. Question for Further Study (RQs): Question 1: Is it possible to use peer evaluation as a grading tool in an electrical engineering class? Using assessment activities other than partial tests, such as making instructional films and having students review each other's work, could improve students' study habits and performance? Approach: Using the Moodle workshop tool, students produce and upload movies to the assigned assignment. The next step is to use a rubric form to conduct peer reviews. Teachers are introduced as anonymous reviewers, and their grading of students' work is compared to that of their students' work to determine the trustworthiness of peer review. Results: The system of evaluation, which is based on evaluations made by peers, showed a fair level of reliability. Despite spending less time studying for the many assessments, participants' academic achievement has improved significantly.

This study, (Qassrawi, 2024), sought to investigate how language instructors at the university level use the Moodle platform for online instruction and how well these methods mesh with the Digital Competence Framework developed in Europe (DigCompEduc). This goal was accomplished by a two-stage data collection process. At first, twenty-five English language instructors from Palestinian universities took part in semi-structured interviews to assess how they used Moodle for online instruction. Afterwards, a checklist developed in line with the European Digital Competence Framework for educators was used to assess these activities. The results showed that teachers' use of Moodle's tools and resources for activities was very uneven. Although some features, like Quizzes and Assignments, were heavily used, others, like Forums, Workshop, and Glossary, were entirely disregarded. Results showed a patchwork of agreement with the framework across domains when it came to how well these online teaching techniques lined up with DigCompEduc competencies. Assessment and teaching techniques were somewhat in sync, but professional involvement, digital resources, instruction and learning, student agency, and the development of students' digital competence were all in discord. Other areas were partially covered, including assessment. Consequently, certain conclusions were made.

This study (Hadyaoui & Cheniti-Belcadhi, 2024) presents the Intelli Frame, a new AI-based framework that will improve the precision and flexibility of student testing. Based on semantic web technologies and a clear ontology, the Intelli Frame allows developing adaptive assessment situations and formative feedback systems in real-time. Such systems can assess the originality, process and critical thinking of AI-assisted tasks to unprecedented accuracy. The architecture of Intelli Frame combines a personalised AI chatbot that communicates with students directly, offering personalised help and creating content that is aligned with course goals. The ontology-based framework design will ensure that besides being personalised, the assessments are also dynamically evolved based on the evolving abilities of generative AI and the cognition of the student. Intelli Frame was tested in a first-year programming course of 250 students. The study found that Intelli Frame had a 30 per cent increase in assessment accuracy, a 25 per cent increase in critical thinking and problem solving, and a 35 per cent increase in student engagement. These results suggest that Intelli Frame can provide quality, personalised assessment and encourage creativity, becoming a new standard of AI-based education testing.

The study (Diahyleva et al., 2025) was dedicated to the analysis of the combination of language and technical skills, the mutual dependence of which is the focus of the study in the educational setting. This study delves into the evolution of modern approaches to teaching Maritime English, specifically highlighting the rise of flexible pedagogical techniques and continuous assessment. Because of the importance of continuously monitoring progress and adjusting teaching methods based on evaluations of language competency, evaluation mechanisms must be in place. In addition to outlining the developments, difficulties, and potential benefits of Maritime English education, this study delves into the effects of online education and digital tools. Future ship engineers must be prepared to function in a global working environment, which is why cross-cultural communication training is so important. Teachers can gain practical ideas from the case studies, best practices, and courses done at the Kherson State Maritime Academy (KSMA), Ukraine. They also talk about the consequences of international standards for maritime language competency. This research highlights the practical benefits of good Maritime English teaching by analysing how these pedagogical tactics affected the crisis management and safety capacities of ship engineers. Researchers recommend that creators of mobile learning apps include features that promote group work, self-evaluation, and personalised comments in order to help students learn as much as possible. In conclusion, Maritime English training should benefit from the integration of online learning resources and technologies (such as Moodle LMS) in order to produce ship engineers capable of meeting the present and future demands of the marine industry.

This study (Pacheco et al., 2025) adopted a learning management system (LMS) to enhance online educational practices and a friendly environment among students based on a qualitative framework and approach of action research. The study was planned in the four steps as follows: Beginning, where goals and hazards were identified and the corresponding technology instrument was chosen; Development, where a first solution was developed and the use case definitions were elaborated; Development, where the remaining criteria were satisfied; They corrected their mistakes and carried out usability tests during the transition, which, as the requirement-checking method. Improving participant management, activity control, teacher-student communication, content availability, and report production led to higher efficiency and quality in the educational service, as revealed by the findings. This research adds to their knowledge of how “Learning Management Systems” (LMSs) can improve educational administration and virtual classroom student learning. Educational institutions that are preparing to adapt to the changing digital landscape can benefit from this research.

This study (Mtakyawa & Banele, 2024) The aim was to present the students' perspectives on the utilisation of Moodle in the classroom at Tanzania's “College of Business Education” (CBE), Dar es Salaam Campus. The study was based on “Connectivism Theory” (CT). Due to its time constraints and reliance on a single case study at CBE, the research opted for a case design. Eleven thousand nine hundred and twenty-four students enrolled in CBE on the Moodle platform were the intended recipients. A total of 374 participants were included in the study by means of probability sampling, more especially simple random sampling. The study included both quantitative and qualitative methodologies. Coding, tabulating, and analysing in MS Excel were used to process the quantitative data obtained from the Likert scale questionnaire. The results for the second and third study questions were also statistically generated utilising tables and figures. Seemingly, after recording and transcribing the qualitative data, it was edited, summarised, tallied, and presented in the narrative. The transcripts were then provided to the respondents for potential error collection. In addition, the qualitative data collected from the semi-structured interviews were analysed using thematic content analysis. The results were then presented using narrative and summary tables. When presenting the answers to each study question, they also made sure to discuss and triangulate the findings.

The results showed that blended learning with Moodle improved comprehension of course materials, and that Moodle's incorporation into the learning process improved the quality of instruction generally. Achieving universal access to high-quality education is a top priority for college administrators and curriculum developers, according to the study. In that regard, they must develop policies promoting the effective application of technology in the classroom, including guidelines on using Moodle in the hybrid learning environment.

### 2.6 Comparative Analysis of Traditional Assessment vs. AI-Based Evaluation Methods

This study (Yazdi et al., 2024) provides a reflective analysis of the role of AI in risk management, providing analogies to traditional risk management practices and the ways in which they could be improved with the introduction of AI and related drawbacks and benefits of the latter. “Convolutional neural networks” (CNNs) are the most fascinating learning technologies that are giving promising results in risk detection and management across several industries because convolutional neural networks can extract valuable information in visual data. A well-planned approach to image selection and processing is part of the study methodology, which also contains three case studies that can be used as references. Case studies like this show how AI can be used instead of picture processing skills to find dangers, evaluate risks, and suggest ways to prevent them. The accuracy, applicability, and practicality of the AI's findings are assessed alongside the system's reaction time and thorough understanding of the situation. According to studies, AI has the potential to greatly improve risk assessment procedures by providing accurate and up-to-date information. The study promotes the interaction between technology and domain-specific knowledge, but it is also cognisant of the fundamental limitations of AI when it comes to contextual interpretation. To guarantee a smooth incorporation of AI into the risk assessment system, additional research is encouraged to build upon the conclusion that AI can revolutionise risk management.

This study, (Alhasan, 2025), explored The efficiency of modern AI methods, namely, Transformer-based NLP models and CNNs in enhancing the accuracy of real-time phishing detection. The study extends and tests the AI-based models to define phishing emails and identify fake websites using textual and visual information. The experiment shows that NLP models, like BERT, based on Transformers, can improve phishing email detection dramatically, as they help to analyse the contextual meaning with a high level of accuracy. Similarly, CNN-based models, such as ResNet and Efficient Net, also demonstrate a high level of performance when it comes to visual analysis of phishing websites. There is an improvement in detection rates compared to using separate models when using a hybrid solution that incorporates textual, URL, and image characteristics. However, in order to make these gains more practically applicable, they still need to solve problems like computational complexity, dataset bias, and model generalisation. By shedding light on AI-driven phishing detection approaches, this research helps advance cybersecurity by providing scalable solutions to deal with new and changing threats. This study highlights the revolutionary potential of machine learning to strengthen digital security by integrating traditional and AI-based methodologies.

This study, (Danda et al., 2024), compares risk management and profit optimisation in cloud-powered financial decision-making for the automotive and healthcare industries using big data and AI. The analysis of healthcare data is expected to inform future public healthcare policy development. In order to make fact-based and accurate healthcare policy decisions, this research analyses whether big data analytics could be systematically integrated into the health policy cycle. This research investigates BDA's potential for accurate and fast healthcare policymaking. PRISMA was used to construct a conceptual framework. BDA in health care policy is introduced, its benefits discussed, a framework presented, examples from the literature introduced, obstacles identified, and suggestions provided. BDA may turn traditional policy-making into data-driven, correct health policy decisions, according to this research. According to this research, BDA may be used in evaluation of health policies, policy identification, development, implementation, and agenda setting. Today, public health policy choices are based on descriptive, predictive, and prescriptive analytics from electronic health reports, public records of health, clinician and patient information, & government as well as social net sites. To use all the information, one must overcome computational, algorithmic, technical, legal, normative, governance, and policy constraints in today's increasingly diverse data world. To maximise its value, big data must be shared. It allows public health organisations and policymakers to assess population-level policy impacts and risks.

This study (Sari et al., 2024) investigated, using a mixed-methods strategy, how adaptive learning systems powered by AI affected educational outcomes in various contexts. Pre- and post-tests, surveys, and system analytics provided the quantitative data, while in-depth interviews yielded the qualitative insights. Three hundred students and fifty teachers from elementary school through university participated. With an average post-assessment score that increased by 14.3 points to 82.7, the data demonstrated that students' performance significantly improved. provides a reflective analysis of the role of AI in risk management, providing analogies to traditional risk management practices and the ways in which they could be improved with the introduction of AI and related drawbacks and benefits of the latter. CNNs are the most fascinating learning technologies that are giving promising results in risk detection and management across several industries because convolutional neural networks can extract valuable information in visual data. Future work should examine the long-term effects, algorithm optimisation, and ethical implications, including the risks involved in potential biases and the privacy issues of the data. It is advisable to standardise references and citations, and format them as this makes them professionally presented. By discussing the practical obstacles and shedding light on how they can be overcome, the present research would form a basis to integrate adaptive learning systems to a greater extent, emphasising their transformative power in establishing inclusive and effective learning conditions. These results promote further research and innovation in the use of AI-driven software to support learning outcomes around the world.

This study, (Rukadikar et al., 2025) aimed It is a comprehensive review of the recruitment evaluation that explores the major theories, analytical methods, procedures, and other vital elements. The work examines 60 research publications through a systematic literature review process, and it summarises the findings using the “theory-context-characteristics-methodology” (TCCM) framework. This study reveals that there was a significant shift in talent acquisition practices in the last 20 years. Though time-honoured, conventional hiring methods have faced a number of challenges, including time-consuming manual screening, subjectivity, and limited access to wider talent pools. Recruitment that is adopted by AI is a potential alternative, bringing about greater speed, objectivity, and personalised experiences with applicants. Based on the SLR and the original synthesis of TAM and RBV, the study proposes a conceptual foundation for additional research. An organisation's ability to make decisions could be improved with the use of AI-based recruiting systems, a user-centred design approach, and the allocation of resources to AI. HR professionals and training programs may help AI professionals become more proficient, and the allocation of resources should be dependent on how useful they are seen to be. This study opens the door for more research on the changing function of AI in HR procedures and adds to their knowledge of talent acquisition tactics.

This study (Nguyen et al., 2025) shows how CNNs outperformed other machine learning models in an automated skin cancer detection test. The CNN model was found to be the most accurate (92.5%), sensitive (91.8%), and specific (93.1%) when compared to other algorithms such as the random forests and the Support Vector Machines (SVMs). The variety of datasets and strong preprocessing methods ensured the robustness and generalisability of the model. Nevertheless, some limitations can be identified even in light of the encouraging outcomes associated with deep-learning-based dermatological diagnoses. Among them are problems of model interpretability and non-homogenous datasets. This study illustrates how AI will enhance precision in diagnosis, result in early detection, and reduce healthcare disparities particularly in low resource settings. Two areas that future research would focus on are improving the explainability of the model and increasing its applicability.

### 2.7 Opportunities and Challenges in Integrating AI-Based Evaluation Tools into Moodle

This study (Kayode et al., 2025) provides a thorough overview of the development of AI in online education, starting with the first automation tools like rule-based intelligent tutors and static content delivery systems and ending with sophisticated personalisation strategies that modify lessons according to students' actions, interests, and level of involvement. Coursera, Duolingo, and Squirrel AI are just a few of the prominent global platforms that showcase AI in education today. The research delves into the fundamental AI technologies, the main areas of AI use in higher education and corporate training, and more. Additionally, the report gives a rundown of some of the most basic evaluation indicators, including personalisation accuracy, engagement, learning gains, and data protection. Both the benefits and the challenges, such as algorithmic bias, the explainability gap, equality concerns, and teacher-AI collaboration, are detailed in the paper. Culturally sensitive personalisation, hybrid human-AI teaching models, and data integration from several learning modalities are some possible avenues for future research. In order to build a future for online education that is intelligent, equitable, and human-friendly, the study ends by urging the responsible, inclusive, and ethical development of AI systems.

This study, (Filiz et al., 2025), investigates the psychological and pedagogical aspects of K-12 teacher willingness to learn and adopt an AI in learning environments. A qualitative, exploratory study was conducted, with 66 teachers of 11 different disciplines in a private school in Turkey taking part in an AI-based teacher professional development program. The data were gathered in online discussion forums and AI-assisted learning activity design tasks and processed with inductive thematic analysis. According to the findings, educators saw AI's usefulness in facilitating personalised learning and lesson planning through its interactive features and flexibility. This was particularly true in the context of ChatGPT and Magic School. But there have been several obstacles, such as problems with technology, curriculum mismatch, ethics, and culture (such as the difficulty to tailor AI-generated content to specific regions). While AI has great promise for improving classroom instruction, the study warns that there are several obstacles that must be overcome before the technology can be fully integrated into the educational system. Research needs to look at many types of schools so they can draw broader conclusions, monitor students over time to see how AI affects their development, and figure out how to incorporate AI into current curricula while still adhering to ethical guidelines.

This study (Moore, 2025) explores how AI is transforming and reshaping instructional design to meet the rapidly evolving needs of the modern education system. By using the foundation of conventional educational frameworks such as ADDIE, Bloom’s Taxonomy, and SAM, the study highlights the limitations of these models in adapting to the significant inputs of AI in enhancing instructional design development and total learning experience in various stages of an individual's educational process. With specific applications, the study has shown how AI integration within the educational framework simplifies instructional methods to enhance inclusive and diverse learning environments. It has also examined various ethical considerations, such as bias in algorithms, to ensure that the integration of AI in education does not violate educational principles and standards. The discussions in the research are supported by practical tools applicable in educational environments, real-world case studies, and an implementation roadmap to guide instructional designers. KEYWORDS: AI, instructional design, 21st century education, personalised learning, AI in education, adaptive learning, learning analytics, generative AI, educational technology, data-driven instruction.

This study (Usher, 2025) compared the grades and feedback provided by AI chatbots, peers, and the course instructor for student projects in a higher education course. The participants were 76 undergraduate students who engaged in a group project involving three phases: questionnaire development, peer assessment, and chatbot-based assessment. Employing a mixed-methods approach, this study quantitatively compared project grades and qualitatively analysed feedback quality. Results indicated that AI chatbots consistently assigned higher grades than human assessors, while peer and instructor grades were notably lower and closely aligned. The content analysis identified that chatbots tended to give more quality feedback than peers, giving a more detailed explanation and offering specific guidance to help improve, but sometimes gave irrelevant or contradictory information that needed the student to intervene. On the other hand, peer feedback was more context-sensitive and personal. These results demonstrate the value of human judgment as a possible solution to overcome chatbot-based assessments limitations and combine the benefits of both approaches to support student learning.

The findings of a pilot program by (Belawati & Prasetyo, 2025) using Gen AI during tutorial sessions at an Indonesian large-scale distance learning institution are detailed in this study. The overarching purpose of the study was to ascertain the effects of Gen AI-based tutoring on student involvement and academic achievement. As an additional objective, they aimed to determine if GAI could automate basic questions and first comments so that human tutors could focus more on moderating and more complex tasks. By combining the OpenAI ChatGPT models (versions 3.5 and 4.0) with the Moodle LMS, the development team was able to complete the work using a modular approach. Three primary modules—Management, LMS Integration, and Backend—made up the finished system. With the help of these modules, the administration was streamlined, the learning platform was easily integrated, and the AI responses in student communication apps were created to perfection. Data was gathered from 37,743 students across four online courses. According to the findings, students in classrooms that utilised GAI had somewhat better grades and were more engaged in class discussions than those in classes that did not. These results indicate that online learning settings can benefit greatly from GAI-based tutor assistants, especially when it comes to increasing student engagement and enhancing their academic performance. To make it even more effective and positively affect student engagement and achievement, the study suggests further improvements.

This study (Hafdi & El Kafhali, 2025) implement EDM in a tertiary institution in Morocco (Hassan First, University Settat, Morocco) in order to improve the quality of education and learning process. To make predictions about the success of students in their initial coding classes, they introduce their own "Hybrid approach" that involves a combination of previous academic success of students plus the information about their behaviour in classes provided by teachers. In order to effectively measure student performance, their study uses numerous ML algorithms, such as multi-classification, data augmentation and binary classification. The key performance measures used to quantify the usefulness of categorisation are F1-score, recall, accuracy, and precision. The findings indicate that the LSTM algorithm can be successfully used to predict the performance of students in their initial learning to code stages providing an 94 percent accuracy rate and F1-score of 0.87 when integrated with a SVM. Besides that, the study proposes an elaborate structure that can be implemented in LMSs to accommodate evolving pedagogies in higher education, alternative pedagogies, and generational changes within the student body. This framework is aimed at assisting schools to adapt to a new development in the field of education whilst maintaining quality and individualised education to students.

The study (Maphalala et al., 2025) helped to collect the relevant content on the given topic that corresponds to the given eligibility criteria and answers the given research questions. The findings explain how AI-motivated e-tutors can transform the game with the use of personalised courses, adaptive criticism, instant help, enhanced motivation and engagement, and better grades. The barriers and limitations that have been taken into account in the study relate to the adoption of AI-based e-tutoring, such as data security, technological access, and continuous optimisation of AI algorithms. Academics, legislators, and tech developers can use the facts and practical suggestions provided by this study to solve a knowledge gap in artificial intelligence (AI) in education and enhance ODeL students' capacity for self-regulation of their learning. Additionally, it discusses the real-world consequences of future studies and practices, as well as the ways in which AI could revolutionise distant learning and give students more control over their own education.

## 2.8 Summary

The adoption of LLMs in Moodle will be a profound change in how educational assessment will be possible within the Indian EdTech market. This research attributes relevance to user perceptions in the uptake and continued utilisation of AI-powered assessment systems by referring to TAM. PU, ease of use, and trust in technology can be deemed as key factors to whether educators and learners are ready to accept automated evaluation systems. TAM provides a systematic perspective with which user behaviour, resistance and acceptance can be analysed and forecasted in the context of digitally transforming learning environment.

In the meantime, AI-enhanced CLT can provide the pedagogic framework of understanding the impact of the use of tools based on LLM on student learning. However, AI-based assessments can pursue constructivist principles of learner-centred and experience-based education by enabling personalised feedback, dynamism, and proactive interventions. Combined, TAM and CLT can create a comprehensive theoretical framework one that examines the issue of technology adoption and the other that examines the outcomes of learning to investigate the potential of AI-driven teaching and evaluation within the Moodle platform, particularly in the context of more effective education delivery and engagement in the EdTech systems of India.

# Chapter III:

# Methodology

## 3.1 Overview of the Research Problem

Digital learning has become a revolutionary force in today's rapidly evolving educational landscape, challenging traditional paradigms of teaching and learning. Digital learning refers to a broad range of methods, including online courses, virtual classrooms, interactive simulations, and adaptive learning systems (Yadav, 2024). Systems like Moodle have since taken centre stage in this shift, providing institutions with a scalable and solid Learning Management System (LMS) (Alomari, 2024). Nevertheless, although Moodle allows for creating a solid digital infrastructure for delivering content and assessment, its assessment methods remain based on traditional pedagogical approaches. These obsolete methods have become increasingly incompatible with the trend of the scalable, personalised and efficient online learning.

**Key limitations in traditional Moodle-based assessment practices include:**

Traditional Moodle-based assessment practices face several challenges that restrict their effectiveness in the Indian EdTech context. While these tools provide a structured framework for testing and grading, they often fail to capture the diverse learning styles, socio-cultural backgrounds, and infrastructural realities of Indian learners. Many students, particularly those from rural or under-resourced areas, experience difficulties in accessing stable internet connectivity or digital devices, which directly impacts their ability to perform consistently in online assessments. In addition, the rigid design of quizzes and assignments may sometimes overlook creativity, problem-solving skills, and critical thinking, which are crucial for holistic learning. Teachers, on the other hand, often find themselves overwhelmed by repetitive grading tasks and limited feedback options, which reduces the scope for meaningful interaction with learners. These limitations create a gap between the potential of Moodle as a powerful LMS and its actual impact in the classroom. The major limitations are summarised in Table 1.

**Table 1**
***Limitations of Traditional Moodle-Based Assessment Practices***

| Limitation | Description | Implications |
|---|---|---|
| **Lack of Personalisation** | Assessments follow a one-size-fits-all approach, overlooking variations in student learning speeds, styles, and needs. | Leads to reduced engagement, demotivation, and poor academic performance. |
| **Labor-Intensive Grading** | Manual evaluation of subjective tasks (e.g., essays, project reports) requires significant educator effort and time. | Delays feedback and prevent teachers from focusing on high-impact activities such as mentoring and instructional design. |
| **Limited Scalability** | Assessment models struggle to keep pace with rising student enrolments in online and blended courses. | Results in late grading and compromised learning experiences. |
| **Inadequate Early Intervention** | Conventional systems lack real-time analytics and predictive tools to identify at-risk learners. | Missed opportunities for timely support, leading to higher dropout rates and academic failures. |

As Table 1 illustrates, the absence of personalisation in traditional assessment frameworks makes it difficult to address diverse learner needs. Similarly, labour-intensive grading practices slow down feedback cycles, which limits opportunities for student improvement. The problem is further compounded by scalability challenges, particularly in the context of rapidly expanding online education in India. Finally, without predictive analytics or real-time monitoring, educators are unable to intervene early, often resulting in higher dropout rates. Collectively, these limitations demonstrate the urgent need for AI-driven solutions that can enhance assessment efficiency, personalisation, and learner support.

These difficulties are particularly intensified in Indian setting, where a large number of students, geographical educational, and infrastructural constraints, and issues complicate the application of efficient digital learning approaches.

This is the scenario in which AI-based evaluation systems that are based on the Large Language Models (LLM), such as GPT-4 and BERT models, can be viewed as a possible solution. These models can analyse student answers, create individual feedback, forecast learning gaps and automate grading, and they can adjust to unique performance patterns.

Although this possibility exists, little is known about the plausibility, flexibility, and success of integrating such AI models into Moodle in Indian educational institutions. There is not much empirical literature discussing the possibility of customising LLMs to the Indian curriculum, regional, or institutional realities.

## 3.2 Operationalisation of Theoretical Constructs

The study operationalises the central theoretical concepts related to the adoption, usability, and perceived effectiveness of AI tools, particularly LLM-based systems, in Moodle settings within Indian schools and universities. These constructs are based on research on the use of AI in education, technology acceptance, and e-assessment frameworks. The constructs were reduced to measurable variables using structured survey items, which can be analysed both qualitatively and quantitatively.

The survey also considered key concepts (e.g., the effectiveness of AI tools) and mapped them to more specific, measurable indicators (e.g., perceived consistency in grading, time saved in evaluation) to ensure comprehensive coverage. Every thematic part of the questionnaire was designed to address a range of constructs, including user experience, systemic issues, and integration opportunities. Perceived effectiveness and usability were assessed using Likert scales, while contextual challenges and future demands were evaluated through open-ended and multiple-choice questions.

To ensure that the study's research questions were translated into measurable dimensions, each theoretical construct was operationalised into corresponding survey variables. Table 2 provides an overview of this process.

**Table 2**
***Operationalisation of Theoretical Constructs***

| Theoretical Construct | Operational Variable |
|---|---|
| **AI Adoption in Moodle** | Use of AI/LLM plugins, frequency of usage |
| **Perceived Evaluation Effectiveness** | Consistency, personalisation, and scalability of grading |
| **User Experience and Usability** | Ease of use, integration with workflow |
| **Institutional and Contextual Challenges** | Issues with manual vs AI grading, support gaps |
| **Future Recommendations** | Suggestions for improving LLM tools in Indian education |

As indicated in Table 2, the research operationalised its theoretical constructs into quantifiable survey items in order to have a clear linkage between conceptual premises and actual data. The indicators used to capture AI Adoption in Moodle included AI or LLM plugin use and frequency of use, whereas Perceived Evaluation Effectiveness included grading consistency, personalisation, and scalability. In the same way, User Experience and Usability was captured in variables that measured how easy the technology is to use and integrate into the current workflow, which focuses on the practical aspect of using the technology. The Institutional and Contextual Challenges construct was investigated with the problems of manual and AI-based grading and institutional support gaps, as well as systemic barriers. Lastly, Future Recommendations enabled the participants to give a recommendation as to how to enhance the use of the LLM tools within the Indian education system, thus integrating a futuristic aspect into the research. This operationalisation, taken together, resulted in translating abstract constructs into measurable, concrete variables in accordance with the purpose of the research.

### 3.3 Research Purpose and Questions

The primary purpose of this study is to explore the feasibility, effectiveness, and contextual relevance of integrating AI-driven evaluation systems—specifically LLMs—into Moodle, within the framework of the Indian EdTech ecosystem. The potential of artificial intelligence (AI) to revolutionise digital evaluation techniques becomes extremely relevant as traditional assessment methods within LMS systems suffer from problems such as restricted scalability, lack of personalisation, and delayed response. The purpose of this study is to determine whether LLM-powered technologies can enhance the quality and effectiveness of online education delivery in India by improving assessment accuracy, automating grading, personalising feedback, and facilitating early intervention techniques for at-risk learners.

To fulfil the objectives of the study, the following research questions will guide the investigation:

- **RQ1** How effective are existing AI-based Large Language Models (LLMs) in evaluating student performance on Moodle in the Indian EdTech context?

- **RQ2** What are the current AI tools and technologies used in Moodle for automated evaluation, and how do they address the unique needs of the Indian education system?
- **RQ3** In what ways can the integration of LLMs into Moodle be optimised to improve teaching methodologies and personalised evaluation in Indian classrooms?

These research questions are designed to capture both the measurable outcomes (such as performance, efficiency, and dropout intervention) and the subjective experiences (such as user acceptance and perceived fairness) of implementing AI-powered evaluations, thereby offering a comprehensive understanding of the model's viability in the Indian educational context.

### 3.4 Research Design

The research design employed in this study is a mixed-methods sequential explanatory design (Fetters & Tajima, 2022). The quantitative part of the research will be followed by a qualitative examination. This strategy is particularly suitable for technology-enhanced educational studies, allowing for a comprehensive understanding of both measurable results and contextual information regarding AI-based assessment systems.

The rationale for choosing a mixed-methods design stems from the dual nature of the research objectives:

- To quantitatively assess the **impact, efficiency, and scalability** of AI-based assessments using structured surveys.
- To qualitatively analyse **user perceptions, challenges, and contextual implications** through secondary literature and previous case studies.

This integration ensures that the numerical data is not interpreted in isolation but is supported by a deeper exploration of existing literature and documented experiences.

To clarify the methodological structure of the study, the design characteristics are summarised in Table 3.

**Table 3**
***Design Characteristics***

| Component | Description |
| --- | --- |
| **Approach** | Mixed-Methods (Sequential Explanatory). |
| **Quantitative Phase** | Google Forms-based surveys are administered to students and educators using Moodle. |
| **Qualitative Phase** | Secondary analysis of academic literature, technical case studies, and EdTech reports. |
| **Integration Point** | Interpretation stage – qualitative findings are used to explain and validate survey results. |

Table 3 demonstrates that the study is explained sequentially according to a mixed-method approach. The quantitative step is a survey of students and teachers in Moodle conducted via Google Forms and, thus, provides primary information on user experiences and AI adoption. It is enabled by the qualitative step that involves the analysis of academic literature, studies, case studies, and reports about EdTech that further develops the contextual and institutional aspects of AI-based assessment. At this stage, these phases intersect to the interpretation stage where the qualitative results may be put into practice and used to support the survey data, in a manner that empiricism may underlie the research findings and applied within the context. The research design adds rigor to the entire study because it very much considers depth and breadth of interpretation of data.

### 3.5 Population and Sample and Participant Selection

The intended sample group of the project includes students and teachers in India who are actively involved in digital learning or assessment activities using Moodle or a Learning Management System (LMS). Since EdTech platforms are increasingly integrated into learning institutions, particularly in higher education and hybrid learning classes, this group is deemed the most suitable to assess the effects and perceptions of AI-powered assessment tools.

The population includes:

- **Students** enrolled in online or blended courses across undergraduate and postgraduate levels.
- **Educators** (faculty members, teaching assistants, or course coordinators) who design, administer, or grade assessments on Moodle.

These stakeholders are the primary users who will be affected by the integration of evaluations based on AI and will serve as the source of both quantitative data (usage and results) and qualitative information (acceptance and challenges) required for the research.

**Sampling Strategy**

Due to the study's specific focus on Moodle and AI exposure, a non-probability sampling method is employed, combining purposive sampling and convenience sampling.

- **Purposive Sampling:** Participants are selected based on their direct involvement with Moodle and their experience with digital or automated assessment tools. This ensures relevance and depth in the data collected (Nyimbili & Nyimbili, 2024).
- **Convenience Sampling:** To accommodate logistical and accessibility constraints, the study also includes participants from institutions that are readily accessible to the researcher, such as partner universities or EdTech collaborators (Isaac, 2023).

This hybrid approach allows the study to reach participants who are both knowledgeable and available, thus balancing relevance with feasibility.

**Sample Size**

Given the niche nature of Moodle adoption in India, particularly with LLM-based assessment tools, the sample size is estimated to be 125 participants. This sample is expected to provide sufficient data to identify trends, draw comparisons, and generate meaningful insights, while acknowledging the exploratory nature of the research.

**Participant Selection**

The target group of the participants in this study was based on the objectives of the research and the necessity to capture rich and relevant information that would be provided by individuals who have direct experience in digital learning and assessment using Moodle. Since the core of this research lies in exploring the viability, efficacy, and user perceptions of introducing evaluation tools based on LLM into the Moodle platform, it was important to engage participants who were not only familiar with online learning systems but also actively involved in using assessment tools in their day-to-day teaching or learning practices. Their voices and lived experiences provided insights that go beyond numbers and statistics, allowing the study to reflect the real opportunities and challenges faced in actual learning environments.

Moreover, involving participants with hands-on experience ensured that the findings were grounded in practical realities rather than abstract assumptions. For instance, teachers could share how existing tools supported—or hindered—their ability to provide timely and meaningful feedback, while students could describe how assessment practices impacted their motivation, confidence, and learning outcomes. To ensure the study remained focused on the most relevant group, clear inclusion and exclusion criteria were carefully designed, as summarised in Table 4.

.

**Table 4**
***Inclusion and Exclusion Criteria***

| | |
|---|---|
| **Inclusion Criteria** | Students currently enrolled in courses delivered through Moodle or similar LMS.<br>Educators (faculty members, lecturers, instructors) using Moodle for assessments.<br>Participants familiar with automated grading systems, quizzes, or AI-assisted features.<br>Willingness to participate and provide informed consent. |
| **Exclusion Criteria** | Individuals not involved in any form of digital or LMS-based education.<br>Participants with no exposure to Moodle or AI-driven assessments.<br>Administrative staff or IT personnel without teaching/learning experience on Moodle.<br>Incomplete or non-consensual survey/interview responses. |

As shown in Table 4, inclusion criteria were focused on students and educators with direct experience of Moodle-based learning and assessment, especially those with knowledge of automated or AI-assisted functions. This attention meant that participants were adequately equipped to deliver valuable information about AI-driven evaluation. Conversely the exclusion criteria left out persons who were not exposed to Moodle, persons who were not involved in teaching or learning and those who did not give full participation or consented to participate. With these boundaries properly spelt out, the study was able to establish the relevancy and validity of the pool of participants.

### 3.6 Instrumentation

The methodology of this study involved the development and construction of an organised online survey to gather both qualitative and quantitative data on the adoption, efficiency, and perception of AI tools, particularly systems based on LLMs, deployed in Moodle environments within the Indian education system. The tool was formulated using Google Forms and focused on gathering the experiences of the concerned users of the tool, including stakeholders such as educators, EdTech professionals, and students.

The instrument, titled **“Survey on AI Tools and LLM-Based Evaluation in Moodle”**, was designed to cover five thematic dimensions:

**Participant Background and Institutional Context** – This section sought to understand who the respondents were and the educational setting they belonged to. It included details such as their role (teacher, student, or professional), type of institution (urban or rural, private or public), and access to digital infrastructure. By grounding responses in their real-world contexts, the survey allowed for a more nuanced interpretation of how institutional differences shape digital adoption and assessment practices.

**Experience with Moodle and AI Plugins** – Here, participants were encouraged to reflect on their hands-on experience with Moodle, including the extent of their familiarity with its features and any prior use of AI-enhanced plugins. This thematic dimension gave voice to teachers managing large classrooms, students navigating online assignments, and administrators exploring efficiency tools. Their practical insights helped highlight where Moodle succeeds and where it falls short in current use.

**Perceived Effectiveness and Usability of AI/LLM Tools** – This section focused on capturing the participants' perceptions of AI integration. Rather than restricting responses to technical measures, it explored human-centred aspects such as ease of use, clarity of feedback, and the sense of trust in automated systems. The responses in this part revealed whether learners felt supported and understood, and whether educators felt that AI genuinely reduced their workload while maintaining fairness and transparency.

**Evaluation Needs and Challenges in the Indian Context** – Recognising the uniqueness of India's educational ecosystem, this dimension invited participants to describe the barriers they face. Issues like inconsistent internet connectivity, digital literacy gaps, and socio-economic constraints were central here. The humanised lens ensured that the survey did not just measure "problems" but recorded how these challenges affected motivation, learning outcomes, and teacher-student interaction.

**Recommendations and Future Directions** – Finally, participants were asked to share their aspirations and suggestions for improving AI-enabled Moodle systems. This section gave them ownership of the research, allowing their voices to shape the vision for future EdTech solutions. Teachers suggested features that could make grading more humane and personalised, students envisioned tools that would keep them motivated, and EdTech professionals emphasised scalability and inclusivity.

In order to allow respondents to provide a wide variety of responses, the survey includes a mix of multiple-choice, Likert-scale, multi-select, and open-ended items. Both qualitative (to obtain the finer details) and quantitative (to understand the patterns and ratings) study benefit from this framework. The major section of this questionnaire is listed in the following Table 5:

**Table 5**
***Survey Sections and Question Types***

| Section | Purpose | Question Types |
|---|---|---|
| Section 1: Background Info | Identifies role, institution type, and Moodle experience. | Multiple choice, single select |
| Section 2: Tool Usage | Captures familiarity with specific AI/LLM plugins and Moodle architecture preferences. | Multi-select, ranking, plugin awareness |
| Section 3: Effectiveness Rating | Assesses perceived impact of AI tools on evaluation consistency, scalability, and personalisation. | Likert scale (1–5), dropdowns |
| Section 4: Challenges Faced | Identifies user-perceived limitations of both manual and AI-assisted grading. | Multiple choice, open-ended. |
| Section 5: Future Directions | Explores recommendations for improving LLM integration in Indian classrooms. | Open-ended, checkbox (multi-select), Likert scale. |

The survey starts with some background questions to capture the profile of the participants as discussed in Table 5 and then is followed by questions related to the use of the tools, but addresses familiarity with AI plugins and Moodle architecture. The third section assesses perceived effectiveness on dimensions of consistency, scalability and personalisation, and the fourth evaluates challenges that the participants faced with the two types of grading systems: a manual and an AI-based grading system. The conclusion is an invitation to think about the future, and it includes a list of items that could be done to make LLM work more effectively in Indian classrooms. All of these components together made it possible for the survey to collect both descriptive and evaluative data, which helped the device meet the overall research goals.

## 3.7 Data Collection Procedures

This study utilised a mixed-methods approach, integrating structured online surveys with secondary qualitative content from scholarly literature, to collect data on the potential, effectiveness, and opinion regarding the incorporation of LLM-based evaluation systems into Moodle, particular within the Indian EdTech context.

### Data Collection Approach

The study employed a sequential explanatory design, with quantitative data collected initially through a survey, while qualitative data was collected via a thematic assessment of literature and industry documents. This method gives a complete picture of the issue at hand by combining numbers with a sense of the situation.

#### a. Quantitative Data Collection (Survey Method)

A structured online survey was the main way this study collected data. Google Forms was used to conduct this survey. It is a trustworthy and easy-to-use platform that makes it easy to gather data, even when participants are spread out across different locations. The survey link was sent out through several different routes, such as academic networks, EdTech forums, institutional mailing lists, and professional social media sites like LinkedIn, to make sure that as many people as possible could take part.

The target group included students, teachers, EdTech administrators, and Moodle developers who worked for schools or organisations that used Moodle or other learning management systems (LMS). The survey questionnaire was meant to collect a complete range of viewpoints by integrating both closed-ended questions—such as Likert scale items and multiple-choice questions—and open-ended prompts that allowed participants to contribute extra qualitative input.

Before starting the survey, all participants were told what the study was about and had to give their informed consent, which is normal practice for ethical research.

**b. Qualitative Data Collection (Secondary Literature Analysis)**

Qualitative information was gathered alongside the central questionnaire using semi-structured interviews and the perusal of secondary materials. Key stakeholders, including educators, EdTech administrators, and Moodle developers, were interviewed, which made it possible to explore their experience and attitudes towards the use of AI-based evaluations and learning management systems in greater depth. These interviews brought forth subtle details of practical issues, implementation strategies, and cultural factors in educational settings.

Moreover, the secondary data collection was conducted through review and analysis of peer-reviewed research articles, technical white papers, and EdTech implementation reports. These sources provided more general insights into practices happening on an international scale but they were also able to outline the curriculum and cultural influences which influenced the adoption of Moodle in India.

The combination of the interview results and the secondary literature analysis complemented the study, triangulating the themes with the survey findings. This method helped not only to confirm the trends observed in the quantitative data but to further elaborate their meaning by combining personal experiences with the developed theoretical background knowledge.

## 3.8 Data Analysis

The research study employed a quantitative data analysis method to analyse the responses of participants in terms of integrating AI, such as LLMs, into learning environments using Moodle. The analysis aimed to identify patterns, associations, and possible impacts of participant characteristics on their perceptions and expectations.

### Software and Tools

The **Statistical Package for the Social Sciences (SPSS)**, version 26, is the software package that was used to analyse all the collected survey data due to its application in statistical analysis in the social sciences and other disciplines. It is characterised by an easy-to-use interface and a full range of statistical tools to manage data, analyse it, and visualise it. It is appropriate in educational research because of the extensive capabilities of conducting descriptive and inferential statistical data analysis in it (Čaplová & Švábová, 2020).

To address the research questions effectively, several statistical techniques were employed, as summarised in Table 6.

**Table 6**
***Statistical Techniques Used in Data Analysis***

| Statistical Method | Purpose | Reference |
|---|---|---|
| **Descriptive Statistics** | Summarise and present features of the dataset. | (Hahs-Vaughn, 2022) (Yellapu, 2019) |
| - Mean & Standard Deviation | Describe central tendency and dispersion for items like Moodle effectiveness. | |
| - Frequencies & Percentages | Report demographic details and closed-ended response patterns. | |
| **ANOVA** | Compare means between user groups based on role or Moodle/AI experience. | (Rouder et al., 2023) (Emerson, 2022) |
| **Pearson Correlation Coefficient** | Examine linear relationships between variables. | (El-Hashash & Shiekh, 2022)(Alsaqr, 2021) |
| **Chi-Square Test of Independence** | Assess the association between categorical variables such as user roles and AI perceptions. | (Berčík et al., 2023)(Kent State University, 2018) |

Table 6 indicates that descriptive statistics, such as means, standard deviations, frequencies, and percentages, were used to give a concise overview of demographics, as well as patterns of responses of participants. ANOVA was applied to compare the mean responses of the group to analyse the differences between them on the basis of the categorisation of these variables: user roles and the level of Moodle or AI experience. Pearson correlation coefficient has been used to examine relationships between continuous variables, whereas a chi-square analysis has been employed to examine associations between categorical variables--relationship between user role and perceptions of AI. All of these statistical approaches meant that the data were considered in a variety of ways, thus adding depth and validity to the results of the research.

### 3.9 Research Design Limitations

This study has some limitations, which must be noted, despite the contribution it makes. The limitation of the findings includes the limitation of generalisation. The study is anchored on a particular sample of Moodle users, teachers and researchers on a small institutional and geographical area. Consequently, the results might not be entirely applicable to other e-learning settings in the world particularly those with other educational systems, cultures or technological systems.

The other weakness is due to the cross-sectional research design. The data were measured at one moment, and it does not allow the formation of causal relations and investigate how the perceptions of the stakeholders and their practices have changed during a long period. Such a time constraint can influence the breadth of knowledge on the development of the attitudes to assessment tools based on LLM.

There is also the limitation of sample size. In as much as the study tried to capture the varied participants, the sample size might not have been enough to capture the broad spectrum of experiences with respect to academic disciplines, the types of institutions and the educational levels. This may inhibit the thoroughness of the findings made out of the data.

Also, the technological experience of respondents could have caused differences in respondent consistency. The differing levels of familiarity with AI tools or Moodle functions might have influenced the participants in the interpretation and answering of the survey questions and create variation in the data.

Lastly, the analysis mainly used quantitative analysis. Although it is an important method that gives quantifiable and replicable results, this may fail to reflect the richness and context of the experiences which the stakeholders go through. Given that qualitative approaches, including the interviews or focus groups, may provide deeper and more comprehensive insight into the issues and perceptions that surround the integration of LLM in Moodle.

### 3.10 Conclusion

The chapter outlined the elaborate research methodology that was adhered to in the effort to examine the integration and performance of the AI- and LLM-based tools within Moodle platforms in Indian education. It described research design, population, sampling strategy, selection of participants and methods of data collection. Both the depth of qualitative research and the rigour of quantitative research were given by the theoretical constructs' operationalisation and instrumentation. The analysis of the data collected was found to be possible using the appropriate statistical methods, i.e., descriptive statistics and inferential statistics. The research methodology is highly adequate to suit the research purpose although consideration of the limitations has been made thus providing solid foundation of future analysis and interpretation in the following chapters.

Chapter IV:

Result

## 4.1 Reliability Analysis of Survey

Cronbach's Alpha coefficient was used in a reliability analysis to ensure the survey instrument employed in this study was internally consistent. This statistical metric evaluates how effectively a collection of objects represents a single, unidimensional latent construct.

**Table 7**
***Reliability Statistics***

| Cronbach's Alpha | N of Items |
|---|---|
| .729 | 12 |

The reliability statistics, as shown in Table 7, indicate a Cronbach's Alpha value of 0.729 for a set of 12 items. This suggests an acceptable level of internal consistency among the items, meaning they are reasonably correlated and measure a common underlying construct. While not exceptionally high, a Cronbach's Alpha above 0.7 is generally considered sufficient for exploratory research, implying that the scale used in the study is reliable for assessing the intended concept.

## 4.2 Frequency Analysis

A frequency analysis was conducted to summarise the distribution of responses across all sections of the survey. This analysis helps identify trends, participation demographics, and key insights related to the adoption and perception of AI/LLM tools in Moodle within the Indian education system.

**Section 1: Background Information**

This section captured the demographic and contextual details of the participants.

**Table 8**
*Participant Background Information*

| Category | Response Option | Frequency | Percent (%) |
|---|---|---|---|
| **Role of Respondent** | Academician | 28 | 22.4 |
| | Educator | 35 | 28.0 |
| | EdTech Administrator | 17 | 13.6 |
| | Moodle Developer | 22 | 17.6 |
| | Student | 21 | 16.8 |
| | Other | 2 | 1.6 |
| **Organization Type** | K–12 Institution | 20 | 16.0 |
| | Higher Education Institution | 58 | 46.4 |
| | Private EdTech Company | 18 | 14.4 |
| | Non-profit / NGO | 27 | 21.6 |
| | Other | 2 | 1.6 |
| **Used Moodle for Assessments?** | Yes | 77 | 61.6 |
| | No | 48 | 38.4 |

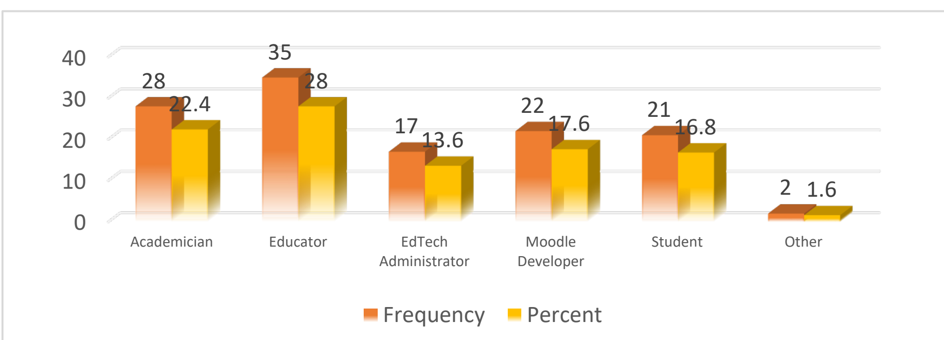


***Figure 4***
***Your Role***

***Note. Created by the author based on survey data (2025).***

Figure 4 presents the distribution of respondents by role, showing that educators comprise the largest group at 28%, followed by academicians at 22.4%. Moodle developers and students account for 17.6% and 16.8%, respectively, while EdTech administrators represent 13.6%. A small fraction (1.6%) selected "Other." This distribution highlights a diverse respondent base, with a strong presence of teaching professionals and technical contributors, reflecting broad stakeholder engagement in the use of Moodle and AI tools within educational settings.

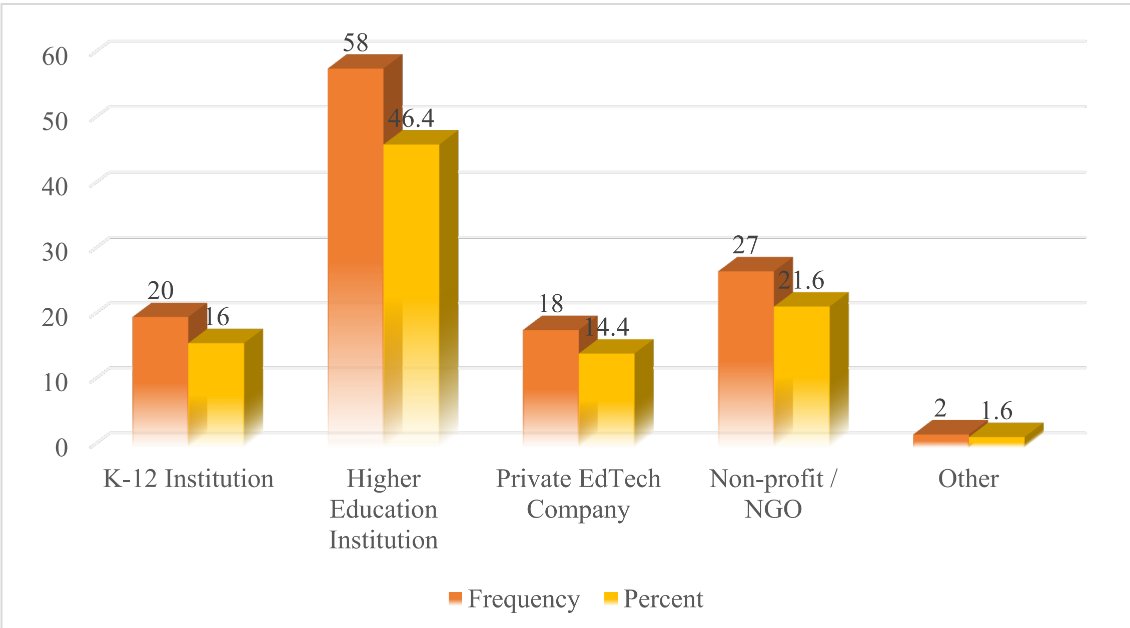


***Figure 5***
***Organisation Type***

***Note. Created by the author based on survey data (2025).***

Figure 5 shows the distribution of respondents by organisation type, with the majority (46.4%) affiliated with higher education institutions. This is followed by participants from non-profit or NGO sectors at 21.6%, and K–12 institutions at 16%. Private EdTech companies account for 14.4% of the total, while only 1.6% represent other types of organisations. The data indicates that higher education dominates the respondent base, but there is also meaningful participation from K–12, non-profit, and private EdTech sectors, reflecting a varied landscape of educational stakeholders involved in AI and Moodle usage.

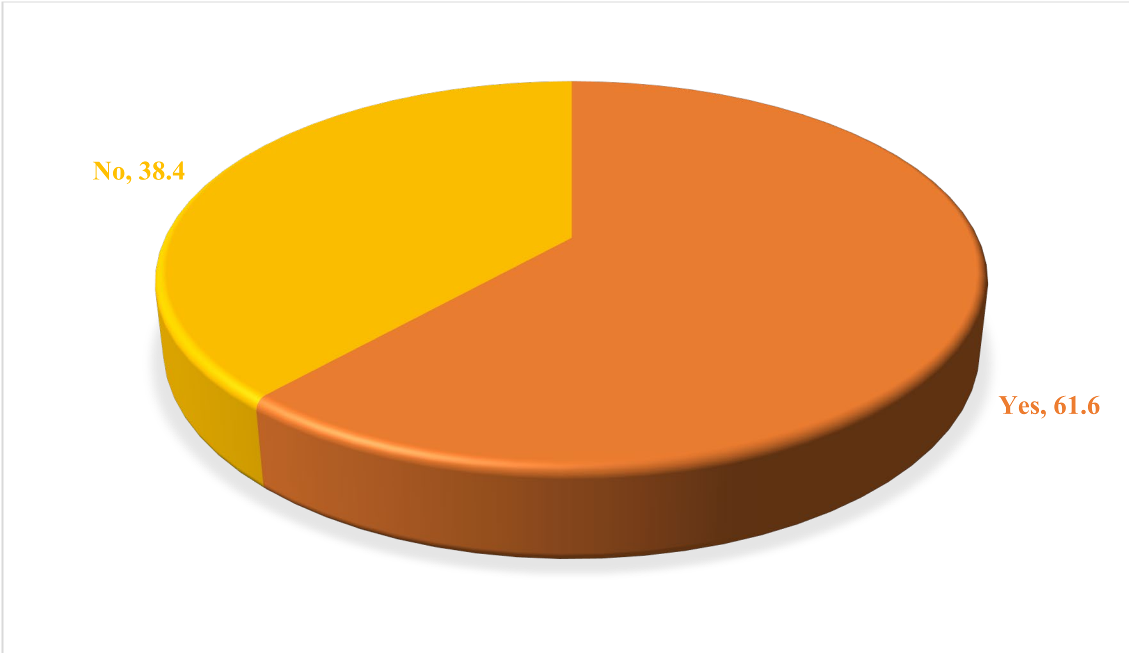


***Figure 6***

***Have you personally used Moodle to create, deliver, or evaluate student assessments?***

***Note. Created by the author based on survey data (2025).***

Figure 6 indicates that a significant majority of respondents (61.6%) have personally used Moodle to create, deliver, or evaluate student assessments, while 38.4% have not. This suggests widespread familiarity and hands-on experience with Moodle's assessment functionalities among users, reinforcing its role as a commonly adopted platform for academic evaluation tasks across diverse educational contexts.

**Section 2: Tool Usage**

This section explores the use of AI-powered tools within Moodle, particularly for automated evaluation and question generation. It also examines users' perspectives on the benefits of Moodle's plugin-based architecture in supporting AI tool integration.

***AI Tools Used in Moodle for Automated Evaluation***

Respondents were asked which Moodle AI tools they have used for automated evaluation.

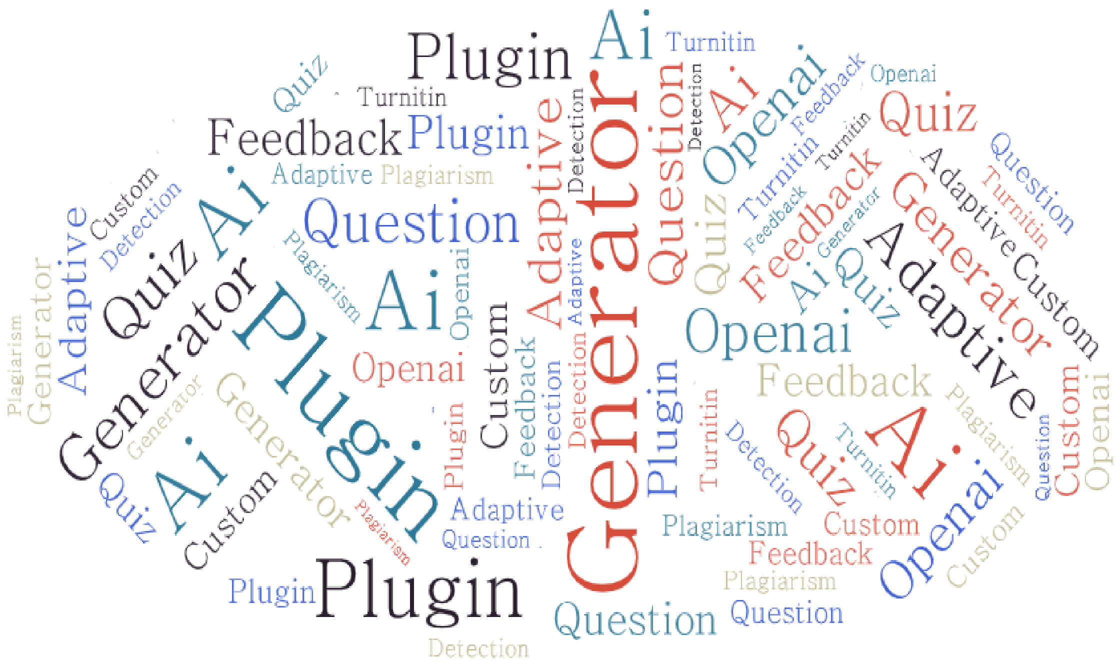


***Figure 7***
***World Cloud of AI Tools in Moodle for Automated Evaluation***
***Note. Created by the author based on survey data (2025).***

Figure 7, a word cloud illustrating AI tools used in Moodle for automated evaluation, highlights that "Generator," "Plugin," "AI," and "OpenAI" are the most frequently mentioned terms, indicating their widespread use among respondents. Other commonly used tools and features include "Question," "Quiz," "Feedback," "Adaptive," and "Turnitin," suggesting a strong focus on content generation, assessment customisation, feedback automation, and plagiarism detection. The prominence of these terms reflects the growing integration of AI-powered plugins and functionalities in Moodle to support efficient and intelligent evaluation processes.

*Perceived Benefits of Moodle's Plugin-Based Architecture*

To understand why users, prefer Moodle's plugin-based design for AI tool integration, respondents were asked to identify the primary benefit of this architecture.

**Table 9**
***What do you see as the primary benefit of Moodle's plugin-based architecture for AI tool integration?***

| Primary Benefits | Frequency | Percent (%) |
|---|---|---|
| It reduces the reliance on core Moodle updates | 25 | 20 |
| It supports a wide range of third-party integrations | 42 | 33.6 |
| It allows institutions to customise LMS features easily | 38 | 30.4 |
| It enables faster performance on older hardware | 20 | 16 |
| Total | 125 | 100 |

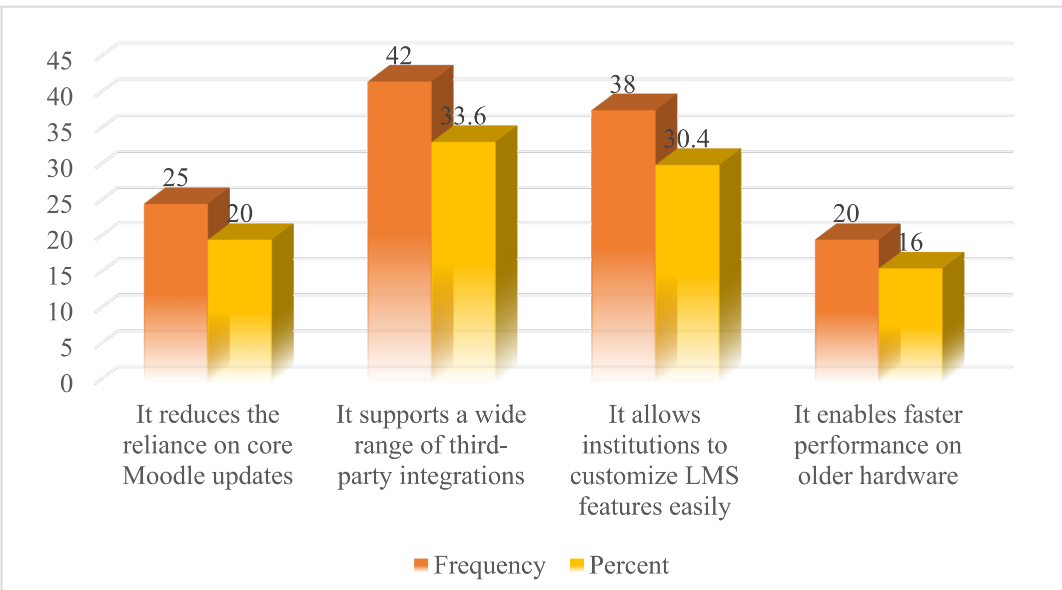


***Figure 8***
***What do you see as the primary benefit of Moodle's plugin-based architecture for AI tool integration?***

***Note. Created by the author based on survey data (2025).***

Figure 8 reveals that the most recognised benefit of Moodle's plugin-based architecture for AI tool integration is its support for a wide range of third-party integrations, cited by 33.6% of respondents. This is closely followed by the ability to customise LMS features easily, selected by 30.4%. A smaller percentage (20%) see reduced reliance on core Moodle updates as the primary advantage, while 16% value the improved performance on older hardware. Overall, the data highlights that flexibility and extensibility—through integration and customisation—are the key strengths appreciated by users in Moodle's plugin-based design.

***AI-Based Question Generation Plugins in Moodle***

Participants were asked to indicate which plugins support AI-based question generation in Moodle.

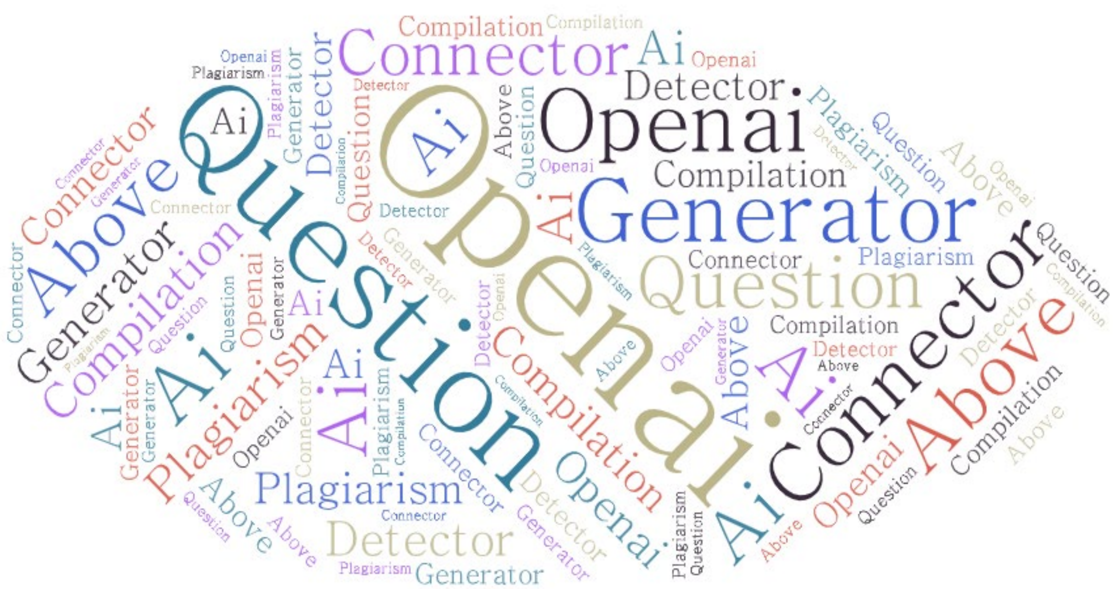


***Figure 9***
***World Cloud of AI-Based Question Generation Plugins in Moodle***
***Note. Created by the author based on survey data (2025).***

Figure 9, a word cloud representing AI-based question generation plugins in Moodle, highlights "OpenAI," "Question," "Generator," and "AI" as the most frequently cited elements, indicating that tools leveraging OpenAI's capabilities are prominently used for automated question creation. Other recurring terms, such as "Plagiarism," "Detector," "Connector," "Above," and "Compilation", suggest a broader ecosystem of AI-powered functionalities integrated into Moodle plugins. Overall, the visualisation reflects a strong presence of generative and evaluative AI tools, emphasising Moodle's adaptability in supporting intelligent assessment design through diverse plugin integrations.

**Section 3: Effectiveness Rating**

This section analyses the respondents' perspectives on the effectiveness and consistency of AI tools, particularly LLMs, in student evaluation and the Indian education context.

**Table 10**
***Effectiveness and Consistency of AI Tools in Evaluation***

| Question | Response Option | Frequency | Percent (%) |
|---|---|---|---|
| **How effective are the AI tools in addressing student evaluation needs?** | Not Effective | 5 | 4 |
| | Slightly Effective | 19 | 15.2 |
| | Moderately Effective | 32 | 25.6 |
| | Effective | 48 | 38.4 |
| | Very Effective | 21 | 16.8 |
| **How consistent is LLM-based grading compared to manual grading by educators?** | Poor | 1 | 0.8 |
| | Fair | 15 | 12 |
| | Good | 35 | 28 |
| | Very Good | 60 | 48 |
| | Excellent | 14 | 11.2 |
| | Multiple-choice questions only | 30 | 24 |

| | | | |
|---|---|---|---|
| **What types of questions do you believe LLMs are most effective at evaluating?** | Essays | 25 | 20 |
| | Short-answer questions | 35 | 28 |
| | Programming/code | 25 | 20 |
| | Case-based/scenario-based | 10 | 8 |
| **How effective are LLMs in addressing scalability issues in Indian education?** | Highly effective | 26 | 20.8 |
| | Effective only for high-income institutions | 27 | 21.6 |
| | Somewhat effective, but needs optimisation | 54 | 43.2 |
| | Ineffective | 18 | 14.4 |

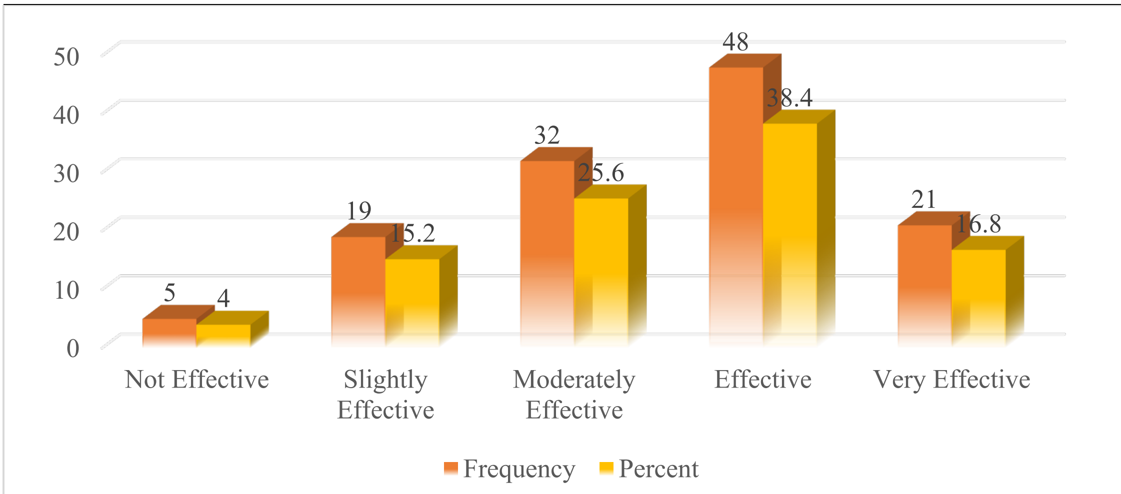


***Figure 10***
***Effectiveness of AI Tools in Student Evaluation***
***Note. Created by the author based on survey data (2025).***

Figure 10 shows that a majority of respondents perceive AI tools as positively contributing to student evaluation needs, with 38.4% rating them as "Effective" and 16.8% as "Very Effective." Additionally, 25.6% consider them "Moderately Effective," indicating a general confidence in their utility. A smaller portion finds them only "Slightly Effective" (15.2%) or "Not Effective" (4%). Overall, the data suggests that most users view AI tools as beneficial for enhancing evaluation processes, though there remains room for improvement in effectiveness and broader user satisfaction.

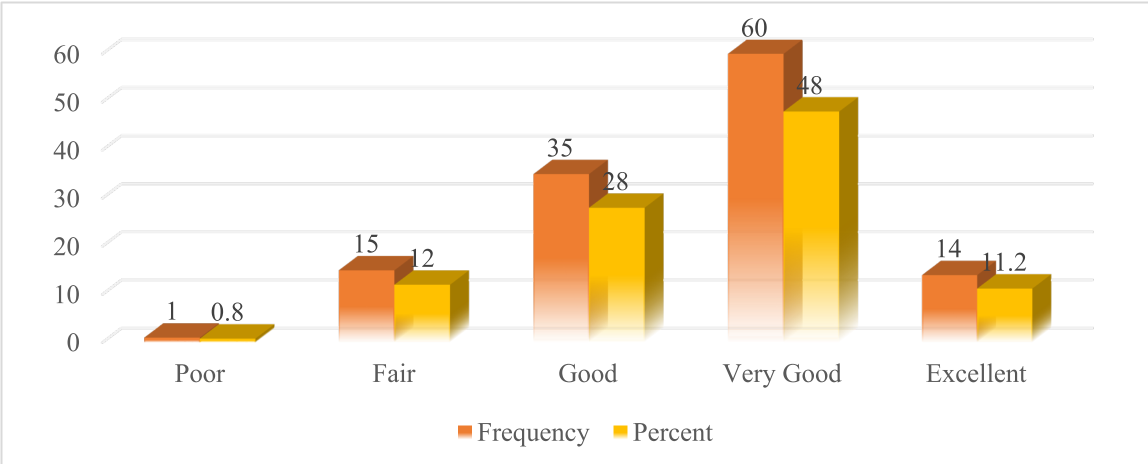


***Figure 11***
***Consistency of LLM-Based vs. Manual Grading***
***Note. Created by the author based on survey data (2025).***

Figure 11 shows that a significant majority of respondents view LLM-based grading as more consistent than manual grading by educators, with 48% rating it as "Very Good" and 28% as "Good." Additionally, 11.2% consider it "Excellent," suggesting strong confidence in the reliability of AI-driven assessment. Only a small portion rated it as "Fair" (12%) or "Poor" (0.8%). Overall, the data indicates that LLM-based grading is generally perceived as highly consistent and potentially more dependable than traditional manual evaluation methods.

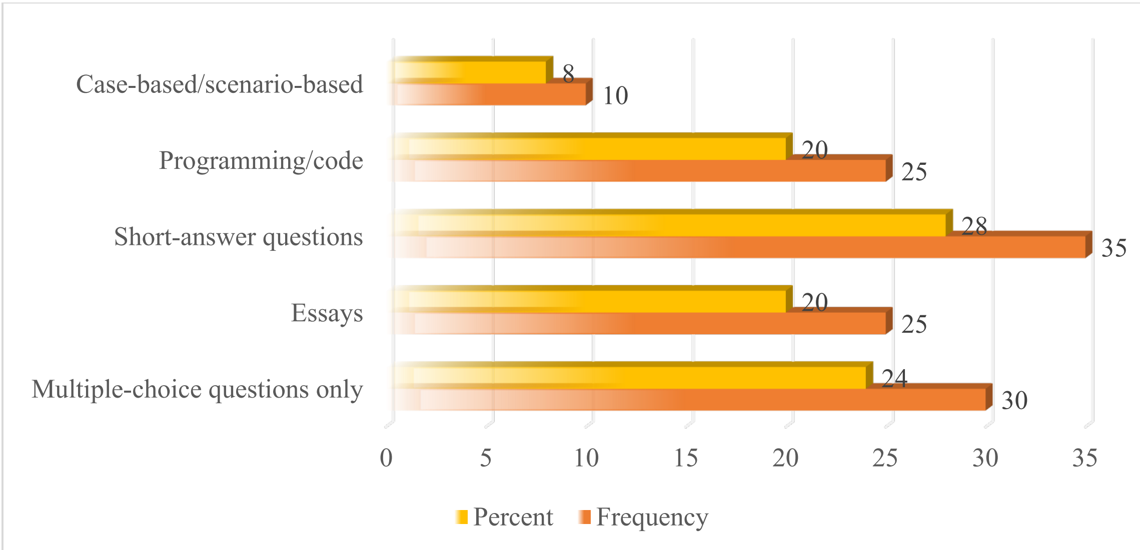


***Figure 12***
***Best-Suited Question Types for LLMs***
***Note. Created by the author based on survey data (2025).***

Figure 12 reveals that respondents believe LLMs are most effective at evaluating short-answer questions, with 28% selecting this option. Multiple-choice questions follow closely at 24%, while essays and programming/code questions are each identified by 20% of participants. Only 8% believe LLMs are most effective at evaluating case-based or scenario-based questions. Overall, the data suggest that LLMs are perceived as most suitable for structured or semi-structured question types, such as short answers and multiple-choice questions, while their effectiveness is seen as more limited in handling complex, context-rich scenarios.

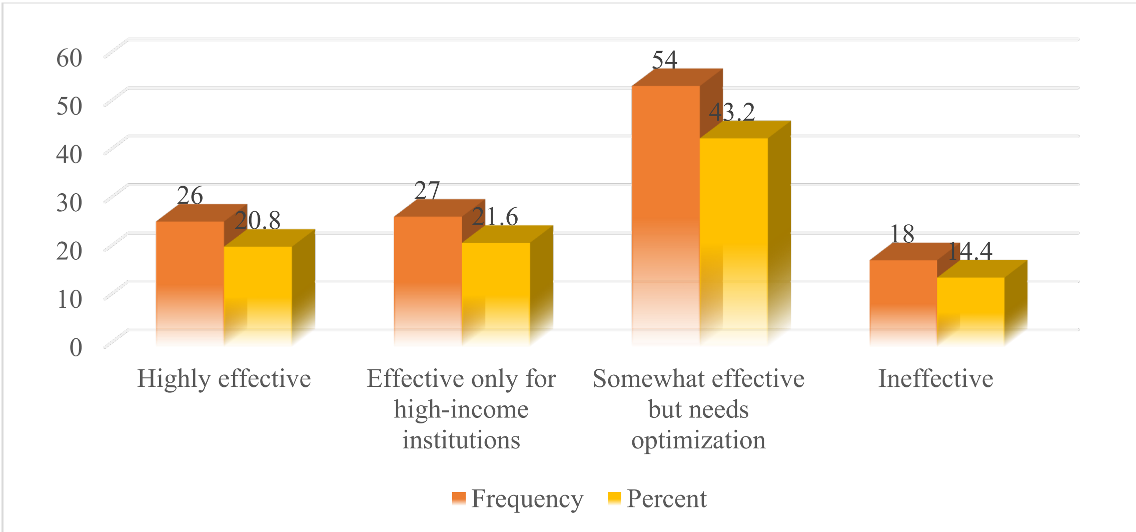


***Figure 13***
***LLMs and Scalability in Indian Education***
***Note. Created by the author based on survey data (2025).***

Figure 13 indicates a divided perspective on the effectiveness of LLMs in addressing scalability issues within Indian education. While 20.8% of respondents believe LLMs are *highly effective*, a slightly higher proportion (21.6%) feels they are *effective only for high-income institutions*. This suggests that while there is recognition of LLMs' potential to enhance scalability, concerns remain about equitable access and the digital divide, highlighting the need for broader infrastructure and support to ensure their benefits reach all educational tiers in India.

**Section 4: Challenges Faced**

The challenges that users encounter when utilising Moodle's AI plugins for assessment are examined in this section. The answers demonstrate the potential and constraints of incorporating AI into evaluation procedures, exposing both pedagogical and technical issues. When comparing AI-based evaluation with manual grading, the information gathered using visual tools, such as word clouds and frequency tables, sheds light on the main issues and perspectives of educators.

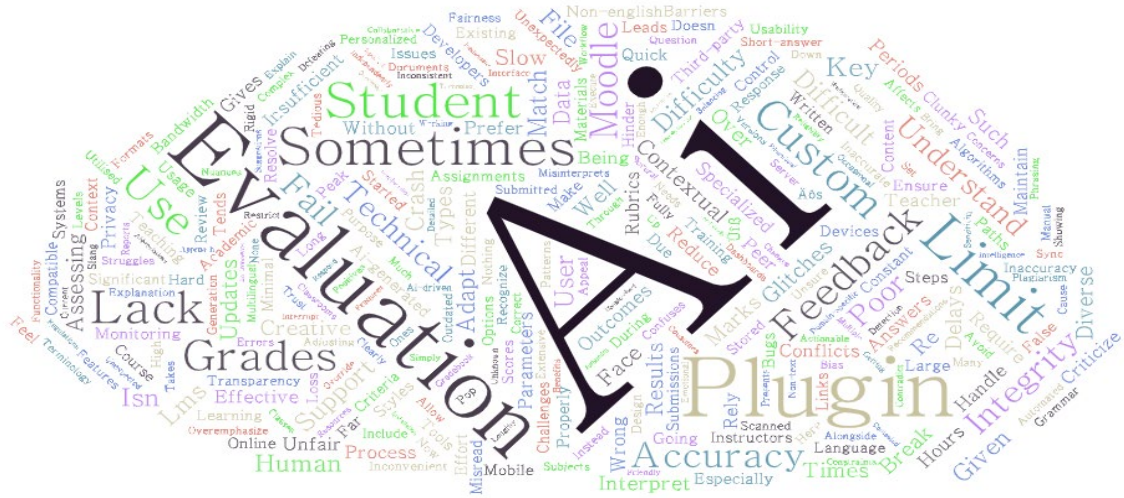


***Figure 14***
***World Cloud of Challenges in Using Moodle's AI Plugins for Evaluation***
***Note. Created by the author based on survey data (2025).***

Figure 14 presents a word cloud of challenges users face when using Moodle's AI plugins for evaluation, with prominent terms such as "AI," "Evaluation," "Plugin," "Grades," "Feedback," and "Limit" indicating key areas of concern. Words like "Sometimes," "Accuracy," "Lack," "Break," "Errors," and "Difficult" reflect issues related to reliability, technical glitches, and limited precision. Additionally, terms such as "Custom," "User," "Integrity," "Glitches," and "Unfair" point to concerns about personalisation, ethical considerations, and consistency. Overall, the visualisation highlights that while AI integration in Moodle offers potential, users encounter significant challenges related to accuracy, system reliability, transparency, and fairness in evaluation.

**Table 11**
***What is the main challenge faced by educators in manual grading?***

| Challenges | Frequency | Percent (%) |
|---|---|---|
| Inconsistency in evaluation | 14 | 11.2 |
| Time-consuming processes | 48 | 38.4 |

| | | |
|---|---|---|
| Delayed feedback for students | 29 | 23.2 |
| All of the above | 34 | 27.2 |
| Total | 125 | 100 |

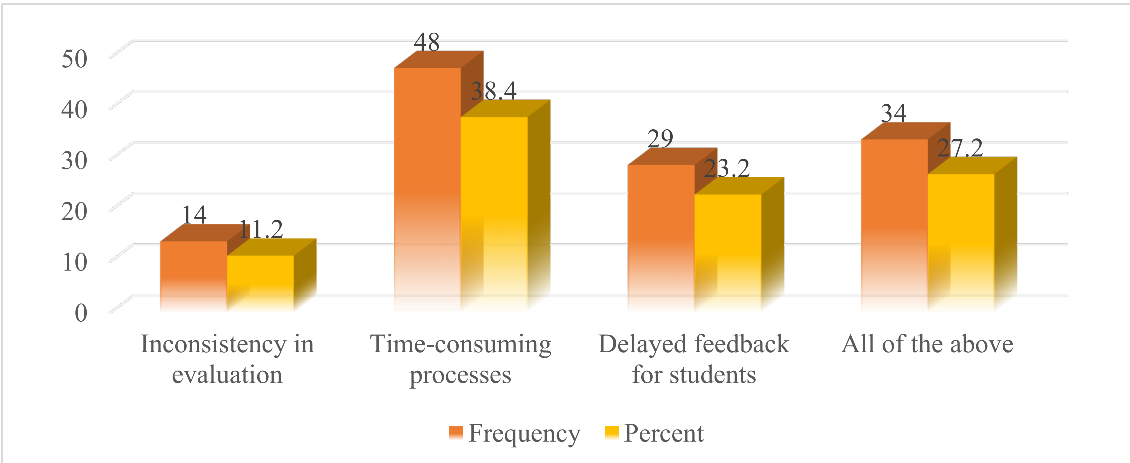


***Figure 15***
***What is the main challenge faced by educators in manual grading?***
***Note. Created by the author based on survey data (2025).***

Figure 15 indicates that the most commonly cited challenge faced by educators in manual grading is the time-consuming nature of the process, selected by 38.4% of respondents. Additionally, 27.2% identified "All of the above," acknowledging that inconsistency, delays in feedback, and time demands collectively impact manual grading. "Delayed feedback for students" was chosen by 23.2%, while 11.2% pointed to "Inconsistency in evaluation" as the primary issue. Overall, the data suggests that efficiency and timely feedback are major concerns in manual grading, reinforcing the potential value of AI tools to streamline assessment processes.


***Figure 16***
***Strengths and Limitations of LLM-Based Evaluation Tools in Your Institution***
***Note. Created by the author based on survey data (2025).***

Figure 16 presents a word cloud summarising the perceived strengths and limitations of LLM-based evaluation tools. Prominent terms such as "Evaluator," "Feedback," "Personalised," "Assess," and "Grade" suggest that speed, automation, and personalisation are viewed as key strengths. However, words like "Sometimes," "Bias," "Limited," "Misinterpret," and "Lack" also appear frequently, indicating concerns about occasional inaccuracies, contextual misunderstandings, and fairness. The coexistence of terms such as "Fast," "Reduce," and "Speed" alongside "Biased," "Inaccurate," and "Critical" highlights the trade-off between efficiency and reliability. Overall, users appreciate the enhanced speed and scalability of LLMs, but remain cautious about their limitations in nuanced educational judgment.

**Section 5: Future Directions**

This section examines participants' perspectives on the potential benefits, enhancements, and context-specific adaptations required for effectively integrating LLMs into Moodle-based learning environments, particularly within the Indian educational context.


***Figure 17***
***Most Significant Benefit of Integrating LLMs into Moodle***
***Note. Created by the author based on survey data (2025).***

Figure 17, a word cloud illustrating the most significant benefits of integrating LLMs into Moodle, highlights "Delivering," "Adaptive," "Learning," and "Experiences" as the most prominent themes. This suggests that respondents view the primary advantage of LLM integration as the ability to deliver personalised and adaptive learning experiences tailored to individual student needs. Other frequently mentioned terms such as "Real-time," "Analytics," "Student," and "Feedback" point to the importance of timely support, data-driven insights, and improved grading capabilities. Overall, the visualisation emphasises that LLMs enhance Moodle by enabling dynamic, student-centred, and scalable educational experiences.

**Table 12**
***What LLM feature is most relevant for personalised evaluation?***

| LLM Features | Frequency | Percent |
|---|---|---|
| Generating adaptive questions | 16 | 12.8 |
| Offering immediate feedback | 36 | 28.8 |

| | | |
|---|---|---|
| Tailoring recommendations to learning styles | 35 | 28 |
| All of the above | 38 | 30.4 |
| Total | 125 | 100 |

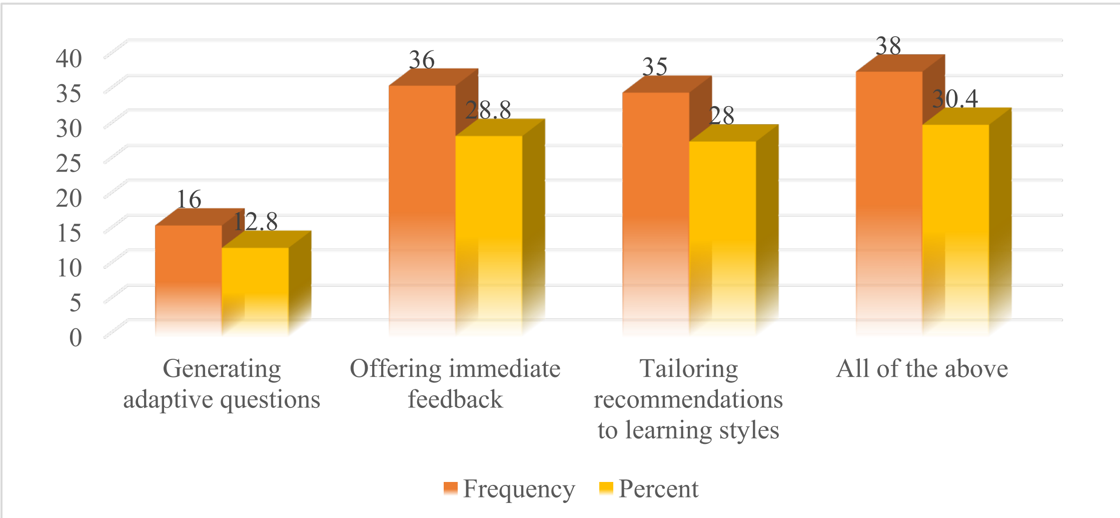


***Figure 18***
***Most Relevant Features for Personalised Evaluation***
***Note. Created by the author based on survey data (2025).***

Figure 18 shows that the most valued feature of LLMs for personalised evaluation is a combination of capabilities, with 30.4% of respondents selecting "All of the above." This indicates strong support for a holistic approach involving adaptive question generation, immediate feedback, and tailored recommendations. Individually, offering immediate feedback (28.8%) and tailoring recommendations to learning styles (28%) were also seen as highly relevant, while 12.8% highlighted adaptive question generation. Overall, the data suggests that educators value LLMs most when they support multiple aspects of personalisation, enhancing the learning experience through responsiveness and adaptability.

**Table 13**
***What would make LLM integration more effective for Indian classrooms?***

| Strategies | Frequency | Percent (%) |
|---|---|---|
| Support for regional languages | 21 | 16.8 |
| Affordable deployment models | 25 | 20 |
| Better teacher training | 28 | 22.4 |
| Mobile-first design for low-connectivity regions | 24 | 19.2 |
| All of the above | 27 | 21.6 |
| Total | 125 | 100 |

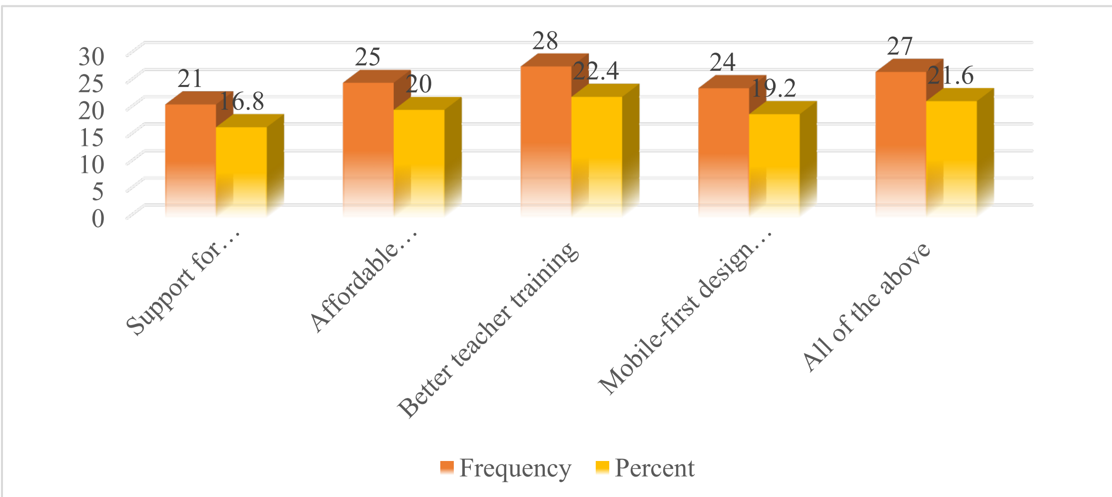


***Figure 19***
***Enhancing LLM Integration in Indian Classrooms***
***Note. Created by the author based on survey data (2025).***

Figure 19 highlights that making LLM integration more effective for Indian classrooms requires a multifaceted approach. The largest share of respondents (22.4%) identified better teacher training as a key enabler, followed closely by those who selected "All of the above" (21.6%), reflecting the need for comprehensive solutions. Affordable deployment models (20%) and mobile-first design for low-connectivity regions (19.2%) were also seen as critical, along with support for regional languages (16.8%). Overall, the data underscores that successful LLM adoption in India depends not just on technology, but also on accessibility, inclusivity, and capacity-building for educators.

**Table 14**
***How important is local content customisation for AI tools?***

| Level of Importance | Frequency | Percent |
|---|---|---|
| Not Important | 4 | 3.2 |
| Slightly Important | 20 | 16 |
| Moderately Important | 26 | 20.8 |
| Important | 57 | 45.6 |
| Very Important | 18 | 14.4 |
| Total | 125 | 100 |

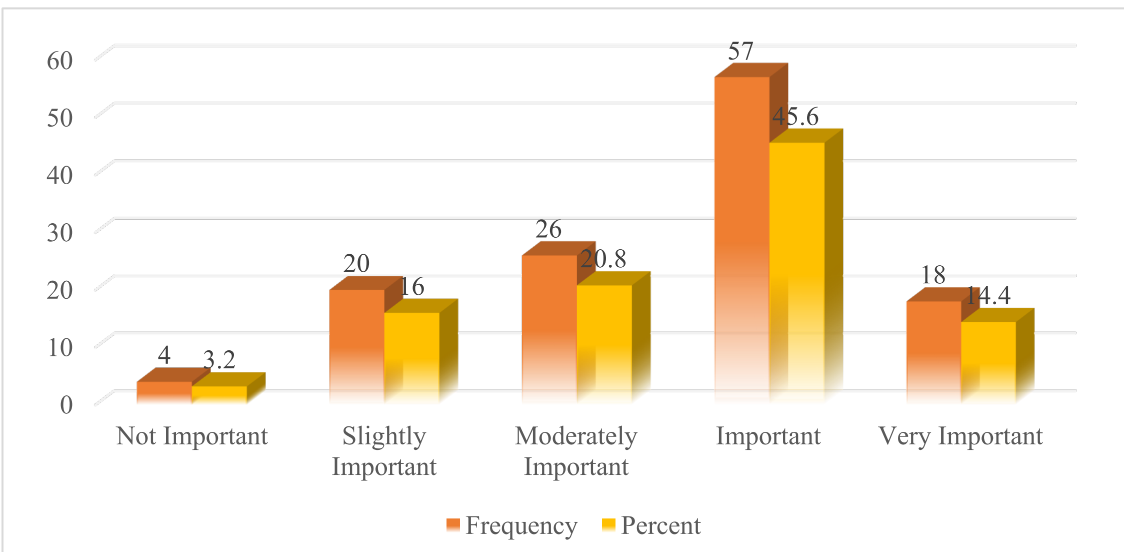


***Figure 20***
***Importance of Local Content Customisation***
***Note. Created by the author based on survey data (2025).***

Figure 20 reveals that a majority of respondents consider local content customisation to be a key factor in the effectiveness of AI tools, with 45.6% rating it as "Important" and 14.4% as "Very Important." Additionally, 20.8% view it as "Moderately Important," while only a small proportion see it as "Slightly Important" (16%) or "Not

Important" (3.2%). This indicates a strong consensus on the need for AI tools to adapt to local contexts, languages, and educational needs in order to be truly impactful and relevant in diverse classroom settings.


***Figure 21***
***Desired Features and Improvements for AI Evaluation Tools in Your Institution***
***Note. Created by the author based on survey data (2025).***

Figure 21, a word cloud of desired features and improvements for AI evaluation tools, highlights "Feedback," "Offline," "Student," "Multilingual," and "Dashboard" as the most frequently mentioned terms. This suggests that institutions prioritise AI tools that can provide accessible, offline-capable feedback, particularly in multiple languages, to better serve diverse student populations. Other important themes include "Grades," "Teacher," "Evaluation," and "Support," pointing to the need for tools that enhance usability for both educators and learners. Overall, the visualisation reflects a strong demand for inclusive, adaptable, and infrastructure-friendly AI features tailored to real-world classroom needs.

## 4.3 Descriptive Analysis of Variables

This section presents the descriptive statistical analysis of key variables related to the use, perception, and effectiveness of Moodle's AI tools and LLM-based evaluation systems in educational settings. The analysis includes measures such as the mean, standard error, standard deviation, and variance for each variable, providing insights into the general trends and variability in responses.

**Table 15**
***Descriptive Statistics***

| Variables | N | Mean | | Std. Deviation | Variance |
|---|---|---|---|---|---|
| | | Statistic | Std. Error | | |
| Your Role | 125 | 2.83 | .131 | 1.469 | 2.157 |
| Organization Type | 125 | 2.46 | .094 | 1.051 | 1.106 |
| Have you personally used Moodle to create, deliver, or evaluate student assessments? | 125 | 1.40 | .045 | .508 | .258 |
| What do you see as the primary benefit of Moodle's plugin-based architecture for AI tool integration? | 125 | 2.42 | .088 | .986 | .972 |
| How effective are the AI tools in addressing student evaluation needs? | 125 | 3.49 | .095 | 1.067 | 1.139 |
| What is the main challenge faced by educators in manual grading? | 125 | 2.66 | .089 | 1.000 | .999 |
| How consistent is LLM-based grading compared to manual grading by educators? | 125 | 3.57 | .078 | .874 | .763 |

| | | | | | |
|---|---|---|---|---|---|
| What types of questions do you believe LLMs are most effective at evaluating? | 125 | 2.68 | .113 | 1.261 | 1.590 |
| How effective are LLMs in addressing scalability issues in Indian education? | 125 | 2.51 | .088 | .981 | .962 |
| What LLM feature is most relevant for personalised evaluation? | 125 | 2.76 | .092 | 1.027 | 1.055 |
| What would make LLM integration more effective for Indian classrooms? | 125 | 3.09 | .124 | 1.391 | 1.936 |
| How important is local content customisation for AI tools? | 125 | 3.52 | .092 | 1.029 | 1.058 |

The descriptive results presented in Table 15 highlight several important trends among respondents. The average rating for the effectiveness of AI tools in addressing evaluation needs was 3.49, indicating a moderately high level of perceived utility. Local content customisation emerged as a particularly significant factor, receiving one of the highest mean scores (M = 3.52), which underscores the strong agreement regarding the importance of contextual relevance in AI-powered tools. Similarly, the consistency of LLM-based grading in comparison to manual grading was positively perceived, with a mean score of 3.57, suggesting confidence in the reliability of AI-supported assessments. Conversely, relatively lower ratings were observed for Moodle usage experience (M =

1.40) and for the perceived scalability benefits of LLMs (M = 2.51), highlighting potential areas for improvement in user adoption and infrastructural support. Moreover, the relatively high variance (Var = 1.936) in responses to the question regarding factors that would enhance the effectiveness of LLM integration in Indian classrooms reflects the diversity of opinions, likely shaped by varied institutional needs and educational contexts. Collectively, these findings provide an essential foundation for the more detailed inferential analysis presented in the subsequent sections of this study.

## 4.4 Hypothesis Testing

The findings of hypothesis testing, which were conducted to assess the connections and discrepancies among the major variables identified in the study, are presented in this section. Depending on the type of variables involved, each hypothesis was investigated using the appropriate statistical techniques, primarily correlation analysis, Chi-square tests, and Analysis of Variance (ANOVA).

**Hypothesis 1:**

- **H01:** There is no significant difference in perceptions across user groups regarding the effectiveness of AI tools and the consistency of LLM-based grading.
- **H1:** There is a significant difference in perceptions across user groups regarding the effectiveness of AI tools and the consistency of LLM-based grading.

**Table 16**
***ANOVA Test Statistics***

| Perception Statement | Source of Variation | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Effectiveness of AI tools in addressing student evaluation needs | Between Groups | 7.069 | 2 | 3.534 | 3.214 | .044 |
| | Within Groups | 134.163 | 122 | 1.100 | | |
| | Total | 141.232 | 124 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Consistency of LLM-based grading vs. manual grading | Between Groups | 2.317 | 2 | 1.158 | 1.530 | .221 |
| | Within Groups | 92.355 | 122 | .757 | | |
| | Total | 94.672 | 124 | | | |

Table 16 presents the results of an ANOVA analysis examining group differences in perceptions of AI tools and LLM-based grading. The analysis reveals a statistically significant difference in how respondents perceive the effectiveness of AI tools in addressing student evaluation needs ($F = 3.214$, $p = .044$), suggesting that responses vary meaningfully across different groups (e.g., roles or organisation types). In contrast, the perceived consistency of LLM-based grading compared to manual grading does not show a significant difference across groups ($F = 1.530$, $p = .221$). This indicates that while views on AI effectiveness differ depending on background or experience, opinions on LLM grading consistency are relatively uniform across the respondent population.

Hence, the alternate hypothesis (H1), which states that there is a significant difference in perceptions across user groups regarding the effectiveness of AI tools and the consistency of LLM-based grading, is accepted.

**Hypothesis 2:**

- **H02:** There is no significant correlation between the perceived relevance of personalised LLM features and the importance placed on local content customisation.
- **H2:** There is a significant positive correlation between the perceived relevance of personalised LLM features and the importance placed on local content customisation.

**Table 17**
***Correlations Between Perceived Relevance of Personalised LLM Features and Importance of Local Content Customisation***

| | | **What LLM feature is most relevant for personalised evaluation?** | **How important is local content customisation for AI tools?** |
|---|---|---|---|
| What LLM feature is most relevant for personalised evaluation? | Pearson Correlation | 1 | .470** |
| | Sig. (2-tailed) | | .000 |
| | N | 125 | 125 |
| How important is local content customisation for AI tools? | Pearson Correlation | .470** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 125 | 125 |

**. Correlation is significant at the 0.01 level (2-tailed).

Table 17 presents the correlation analysis between the perceived relevance of LLM features for personalised evaluation and the importance of local content customisation. The results show a moderate positive correlation ($r = 0.470$) that is statistically significant at the 0.01 level ($p = .000$). This indicates that respondents who consider personalised features such as adaptive questions and tailored feedback to be important are also more likely to value local content customisation in AI tools. The finding suggests a clear linkage between personalisation and localisation needs, highlighting the importance of context-aware AI solutions in educational settings.

This means that the alternate hypothesis (H2), which states that there is a significant positive correlation between the perceived relevance of personalised LLM features and the importance placed on local content customisation, is accepted.

**Hypothesis 3:**

- **H03:** Educators' perceptions of LLM effectiveness in addressing scalability challenges do not vary significantly based on Moodle usage or grading challenges.
- **H3:** Educators' perceptions of LLM effectiveness in addressing scalability challenges vary significantly based on Moodle usage or grading challenges.

***Relationship Between Moodle Usage and Perceptions of LLM Effectiveness in Addressing Scalability***

To assess whether practical experience with Moodle influences perceptions of LLMs' effectiveness in addressing scalability challenges in Indian education, a cross-tabulation and chi-squared test were conducted.

**Table 18**
***Crosstab and Chi-Square Analysis Between Moodle Usage and Perceived LLM Effectiveness***

| | | **Have you personally used Moodle to create, deliver, or evaluate student assessments?** | |
|---|---|---|---|
| | | **Yes** | **No** |
| How effective are LLMs in addressing scalability issues in Indian education? | Highly effective | 17 | 9 |
| | Effective only for high-income institutions | 17 | 10 |
| | Somewhat effective but needs optimisation | 32 | 22 |
| | Ineffective | 11 | 7 |
| Total | | 77 | 48 |
| **Pearson Chi-Square** | | | **1.716** |
| **Sig.** | | | **0.944** |

Table 18 presents the cross-tabulation between respondents' experiences using Moodle and their perceptions of LLMs' effectiveness in addressing scalability issues in Indian education. Among those who have used Moodle ($n = 76$), a large proportion rated LLMs as "Somewhat effective but needs optimisation" ($n = 32$) or "Highly effective" ($n = 17$), reflecting cautious optimism. Similarly, non-users ($n = 48$) predominantly chose "Somewhat effective but needs optimization" ($n = 22$), indicating that both groups generally recognise the value of LLMs but acknowledge room for improvement. Chi-Square test results indicate no statistically significant association between Moodle usage and perceived LLM effectiveness (Pearson $\chi^2 = 1.716$, $p = .944$). Overall, these findings suggest that firsthand experience with Moodle does not significantly influence respondents' views on the scalability potential of LLMs in the Indian education context. This suggests a shared perception among user groups that while LLMs hold promise, strategic refinement and contextual optimisation remain essential for broader adoption.

***Relationship Between Perceived Manual Grading Challenges and LLM Effectiveness in Addressing Scalability***

A cross-tabulation and chi-squared analysis were used to investigate if educators' opinions regarding the scalability and efficacy of LLMs in Indian education are influenced by their perceptions of the difficulties associated with manual grading. The purpose of the study was to determine whether respondents' perceptions of how well LLMs handle large-scale assessment demands were correlated with certain grading-related pain points, such as inconsistent results, time consumption, or delayed feedback.

**Table 19**
***Crosstab and Chi-Square Analysis Between Perceived Manual Grading Challenges and LLM Scalability Effectiveness***

| | | **What is the main challenge faced by educators in manual grading?** | | | |
|---|---|---|---|---|---|
| | | **Inconsistency in evaluation** | **Time-consuming processes** | **Delayed feedback for students** | **All of the above** |
| How effective are LLMs in addressing scalability issues in Indian education? | Highly effective | 2 | 11 | 4 | 9 |
| | Effective only for high-income institutions | 6 | 13 | 7 | 1 |
| | Somewhat effective but needs optimisation | 6 | 21 | 14 | 13 |
| | Ineffective | 0 | 3 | 4 | 11 |
| Total | | 14 | 48 | 29 | 34 |
| **Pearson Chi-Square** | | **22.981** | | | |
| **Sig.** | | **0.006** | | | |

Table 19 presents the cross-tabulated responses showing the distribution of LLM effectiveness ratings across various challenges faced in manual grading. Respondents who selected "Time-consuming processes" or "All of the above" as their primary concern were more likely to view LLMs as "Highly effective" or "Somewhat effective but needs optimisation." In contrast, those who identified "Delayed feedback" or "Inconsistency" expressed more varied opinions, with a slight increase in those viewing LLMs as ineffective.

The Pearson Chi-Square value of 22.981 with a p-value of 0.006 indicates a statistically significant association between the type of manual grading challenge perceived and the respondent's view on LLM effectiveness for scalability. This suggests that educators' pain points in grading indeed influence their perception of the value of LLMs. Specifically, those who struggle most with time and workload appear more optimistic about LLM-based solutions for scalability, highlighting a potential alignment between technology offerings and actual educator needs.

Conclusively, the findings indicate that Moodle usage does not significantly influence educators' perceptions of LLM scalability ($p = 0.944$), while perceptions do vary significantly based on manual grading challenges ($p = 0.006$). Therefore, Hypothesis 3 is partially accepted—rejected for Moodle usage, but accepted for grading-related variation.

**Hypothesis 4:**

- **H04:** There is no significant difference in the perceived requirements for effective LLM integration based on respondents' roles or their Moodle experience.
- **H4:** There is a significant difference in the perceived requirements for effective LLM integration based on respondents' roles or their Moodle experience.

***Relationship Between Respondents' Roles and Perceived Requirements for Effective LLM Integration***

To evaluate whether professional roles influence what stakeholders believe are the key requirements for successful LLM integration in Indian classrooms, a cross-tabulation and chi-squared test were applied.

**Table 20**
***Crosstab and Chi-Square Analysis Between Respondent Role and Perceived Requirements for LLM Integration***

| | | What would make LLM integration more effective for Indian classrooms? | | | | |
|---|---|---|---|---|---|---|
| | | **Support for regional languages** | **Affordable deployment models** | **Better teacher training** | **Mobile-first design for low-connectivity regions** | **All of the above** |
| Your Role | Academician | 4 | 8 | 6 | 2 | 8 |
| | Educator | 5 | 7 | 5 | 12 | 6 |
| | EdTech-Administrator | 5 | 1 | 5 | 4 | 2 |
| | Moodle Developer | 4 | 6 | 8 | 2 | 2 |
| | Student | 3 | 3 | 4 | 4 | 7 |
| | Other | 0 | 0 | 0 | 0 | 2 |
| Total | | 21 | 25 | 28 | 24 | 27 |
| **Pearson Chi-Square** | | **28.543** | | | | |
| **Sig.** | | **0.097** | | | | |

The cross-tabulation of respondents' professional responsibilities and their opinions on the essential conditions for successfully implementing Large Language Models (LLMs) in Indian classrooms is shown in Table 20. The most often selected answers across all categories were "Better teacher training" (n = 28) and "All of the above" (n = 27), indicating widespread agreement on the complex requirements for an effective LLM deployment. Teachers' strong choice for "Mobile-first design for low-connectivity regions" (n = 12) underscored the importance of grassroots infrastructure issues. On the other hand, Moodle developers and edtech administrators highlighted "Better teacher training" and "Support for regional languages," pointing to linguistic and technological obstacles to acceptance. Respondent positions and reported integration needs appear to be somewhat but not statistically significantly correlated, according to the Pearson Chi-Square value of 28.543 at a significance level of 0.097. This suggests a range of inconclusive role-based variations in the order of importance of LLM implementation tactics.

***Relationship Between Moodle Experience and Perceived Requirements for Effective LLM Integration***

To explore whether Moodle experience influences opinions on the factors necessary for effective LLM integration, a cross-tabulation with chi-squared testing was conducted.

**Table 21**
***Crosstab and Chi-Square Analysis Between Moodle Experience and Perceived Requirements for LLM Integration***

| | | **What would make LLM integration more effective for Indian classrooms?** | | | | |
|---|---|---|---|---|---|---|
| | | **Support for regional languages** | **Affordable deployment models** | **Better teacher training** | **Mobile-first design for low-connectivity regions** | **All of the above** |
| Have you personally used Moodle to create, deliver, or evaluate student assessments? | Yes | 13 | 15 | 14 | 17 | 18 |
| | No | 8 | 10 | 14 | 7 | 9 |
| Total | | 21 | 25 | 28 | 24 | 27 |
| **Pearson Chi-Square** | | **6.303** | | | | |
| **Sig.** | | **0.613** | | | | |

Table 21 investigates whether opinions of the prerequisites for the successful integration of LLMs in Indian classrooms are influenced by past Moodle experience. The respondents were divided into groups according to whether they had created, delivered, or evaluated student assessments using Moodle. Similar preferences were noted between the experienced and inexperienced groups, with "All of the above" and "Better teacher training" regularly earning high scores. For example, 14 members of each group indicated that "Better teacher training" was essential, whereas 18 Moodle-experienced users and 9 non-users chose "All of the above."

There is no statistically significant correlation between Moodle experience and the perceived needs for LLM integration, as indicated by a Pearson Chi-Square value of 6.303 at a significance threshold of 0.613. This implies that respondents have largely similar opinions about what is necessary for an LLM to be successfully implemented in classrooms, irrespective of their level of Moodle experience, highlighting the universality of the problems across user groups.

Conclusively, there is no statistically significant difference in perceived requirements for effective LLM integration based on either respondent roles or Moodle usage. While some role-based preferences emerged, the associations were not strong enough to support Hypothesis 4. Therefore, the null hypothesis (H04) is accepted.

# Chapter V:

# Discussion

## 5.1 Discussion of Results

The findings of this study reveal complex and conflicting opinions among stakeholders about the utilisation of Large Language Model (LLM) tools for student evaluation in Moodle. While educators, developers, and administrators exhibited varying levels of optimism, there was a consensus on the possibility of LLMs to provide greater uniformity in grading compared to manual review. However, this agreement should not be construed as total approval. The findings show some concerns: stakeholders said that consistency is a good thing, but they were worried about the loss of awareness of context in automated grading, trust, and fairness. There is a struggle across efficiency and the human touch that is similar to what is being talked about in other parts of the world about using AI in education. Yet, it seems to be particularly significant in India, where culture and language are important parts of assessment.

Another crucial lesson is that personalisation and localisation are very closely related. Those who valued adaptable, learner-centred attributes consistently emphasised the value of regional language support and content customisation. This correlation highlights one of the core needs of context-sensitive AI design in Indian EdTech: in the Indian EdTech context, personalisation is inseparable from localisation. Although the international literature on AI in education often emphasises the universally positive effects of personalisation, the current research demonstrates that in India, personalisation, unless accompanied by cultural and linguistic conformity, is an aspect that may be viewed as irrelevant or inaccessible. This is a sign of knowledge gap in the available literature, which is overly concerned with technical scalability without paying enough attention to socio-linguistic adaptation.

Interestingly, pre-existing familiarity with Moodle did not have much impact on the respondents' perception of the need to scale or integrate LLM. This counters the belief that explicit platform familiarity influences attitudes towards the adoption of AI. Rather, it was more the lived experiences of teachers with manual grading. People who find evaluations that take up a lot of time to be a burden were more likely to see LLMs as scalable solutions. This study has an essential implication: being open to using AI does not correlate to how much technology someone uses, but rather to how big challenges are in the way education is done. Consequently, policies and implementation strategies must be formulated to concentrate on decreasing real workload pressures, instead of relying on the assumption that training or previous system usage will inherently facilitate adoption.

Lastly, despite various professional groups noting different priorities in terms of integration (e.g., mobile-first design in teachers or regional language support in developers), statistical tests did not support role-based differences. That means that there is a unanimous understanding of the essential needs of successful LLM integration at different perspectives, even though they may differ. This coincidence of priorities indicates that, as a rule, there is a realisation of the systematic problems in Indian education, especially the digital gaps and infrastructure constraints. However, the fact that the difference was not significant also suggests that there might be a constraint: as soon as all groups are interested in the same needs, there are the chances that the more specific or role-related needs will be under-researched, which will create a gap in the implementation strategy tailoring.

Collectively, the results suggest that although stakeholders view LLMs as potentially beneficial in improving the consistency of grading, personalisation, and scalability, they do not endorse blind implementation. Results are consistent with the existing literature about the benefits of AI in terms of its efficiency, but different in its focus on the importance of localisation and infrastructural realities. This indicates that the future of AI-based assessment in Indian classrooms will not entirely rely on the level of technical development but will be based on the capacity to localize the tools to cultural, linguistic as well as systemic backgrounds.

## 5.2 Discussion of Research Question One

The findings of Research Question One reveal a lack of consensus among stakeholders regarding the efficacy of LLM-based grading in Moodle. Differences between groups suggest that professional function and exposure affect expectations. Some stakeholders mentioned the benefits of increased efficiency, while others raised concerns about trust, bias, and the moral issues of automating evaluation. This disparity shows that using AI technologies in education isn't only a technical procedure; it's also significantly influenced by the culture of the institution and the professional identity of the people employed there.

One of the main things that can be learnt from this research is that LLMs can help make it easier to criticise large-scale grading. As (Fagbohun et al., 2024)Furthermore, human grading is a bottleneck in systems with big student-to-instructor ratios. LLM-based grading is also scalable and uniform, which is hard to do with a few people, particularly in India, where the classroom population is big and variable. This assurance has limits though, because of the risk of algorithm bias and the lack of a reasonable moral norm to oversee computerised assessment. Although the disparity in an LLM can be minimised, it can also reproduce or increase the existing disparities when the training data is not selectively edited to fit the Indian contexts.

Furthermore, the capacity to grade and to provide personalised, timely feedback is also considered a valuable feature of LLM-enabled systems. (Meyer et al., 2024) report feedback is related to improved learning outcomes and student motivation, which is also consistent with the findings of this study. Indian learners, particularly when they are in a self-paced course in Moodle with little access to ongoing teacher mentorship, the immediacy of AI-generated feedback may be a game-changer. Nevertheless, the threat is overdependence: in case the AI-feedback replaces, instead of complements, the teacher feedback, the human aspect of the pedagogical process can be threatened.

Another important advantage was the uniformity of grading with AI. Respondents appreciated the elimination of subjective variability that is a bane of manual judgment. However, this advantage needs to be looked into. Consistency is indeed a good way of promoting fairness, but it does not necessarily imply equity. Linguistically diverse or under-resourced students can also fall behind in using non-standard phrasing or culturally-specific arguments when the LLM does not understand them. In this way, the same aspect that makes fairness at scale better can also unintentionally suppress diversity in student responses.

Lastly, individualisation was mentioned as a valuable expectation of AI-based evaluation. Studies such as (Bhutoria, 2022; González-Calatayud et al., 2021) argue that digital education can be more inclusive through adaptive, learner-centred pathways. This aligns with the findings of the present study, since stakeholders emphasised that evaluation must be tailored to the individual needs of a student. But in the Indian EdTech sector, personalisation can't happen without localisation. Personalisation might be shallow without supporting regional languages and contextual content. RQ1 illustrates both the potential and the difficulties of LLMs: they can offer scalable, consistent, and adaptable evaluation, but only if they are crafted to be attuned to the sociocultural diversity present in Indian classrooms.

## 5.3 Discussion of Research Question Two

The findings of Research Question Two suggest that personalisation in AI-driven assessment can't be considered in isolation; it must be integrated with localisation to effectuate major changes in Indian classrooms. This dual demand is illustrated by the association between respondents' desire to use adaptive features and their focus on regional content customisation. Personalisation can improve student involvement on its own, but if language, cultural, and curricular settings are not taken into account, it is likely to become a universal approach with little to no sophisticated relevance. This echoes (Souali et al., 2019), who say that AI-based learning environments should be flexible enough to fit with local practices instead of assuming that they work everywhere.

Moodle's open-source and modular design also makes it possible to do this on a technological level. Plugins that are in line with Indian curricular norms, including those that make questions that are applicable to a certain area or those that foster learning in over one language, are examples of how customisation and localisation work together. But the results also show a big problem: while if some technologies, like question makers based on OpenAI, can technically make suitable material, they might not be able to grasp the nuances of regional semantics or student conduct in non-Western settings. According to (Kizilcec, 2024) Generalised NLP models also deal with multilingual complexity, which is especially applicable in India.

The emphasis on localised individualisation reflects systemic challenges within Indian higher education as a whole. (Hooda et al., 2022) Say that AI should be used on a scale that takes into account socioeconomic diversity and infrastructure limits, not only what is best for teaching. The results of this study support the notion that personalisation is advantageous, but only when incorporated into systems that are attuned to cultural and language contexts. You can use tools like Intelliboard and X5-Moodle to make responsiveness work by giving you real-time tracking and remedial feedback. But these systems create new questions of feasibility and equity: can resource-constrained institutions avail themselves of them, or will the benefits of localisation continue to be concentrated in high-resource environments?

Finally, while recent scholarship such as (Zastudil et al., 2023) highlights passion and precaution about the use of LLM in education. This study expands the debate by revealing how Indian stakeholders conceptualise personalisation and localisation as two inseparable concerns. Instead of considering AI as a tool to automatize work, the respondents mentioned identity recognition and contextual relevance to be the key aspects of successful implementation. This is an indication of a break with much of the world literature, where technical efficiency is at times given preference over cultural appropriateness. The problem in the Indian EdTech market isn't that learning needs to be more personalised; it's that personalisation needs to be done in a way that respects and shows the diversity of learners.

## 5.4 Discussion of Research Question Three

The findings of Research Question Three demonstrate a significant correlation between the perceived utility of integrating LLMs into Moodle and the level of difficulty teachers experience in grading. as teachers who had to deal with constant delays and heavy workloads were asked about how comfortable they were in the evaluation aided by LLM, they indicated it was a way to relieve stress and not just a way to automate mundane tasks. This reflects a broader comprehension of the literature: AI signifies a pedagogical prospect not solely through the complete substitution of human labour, instead through a systematic initiative to eradicate inefficiencies that affect teaching quality (Zubairi et al., 2021a). This perspective sees LLMs as tools for improving teaching, not as alternatives for technology.

The lack of a clear link between past Moodle use and favourable feelings about the LLM implementation makes it exceedingly difficult to support the idea that being familiar with technology inherently leads to a desire to use AI. Unlike (Kizilcec, 2024)The study contends that the determinants of adoption are more contextual in India, highlighting a stronger association between platform experience and perceived AI benefits. The inequalities in institutional resources, infrastructure, and other factors that affect how much technology people have access to to mean that user experience is not a good way to tell if something is accepted. This shows why AI design should be responsive to workflows: Plans for integration need to take account of real bottlenecks and not just assume everybody is ready because they understand Moodle.

The results also show how important it is to include a diverse group of stakeholders in the integration efforts. While teachers concentrated on responsive solutions to make things easier to use, developers focused on training needs, and leaders focused on making things bigger. These differences mean that optimisation needs coordinated design models, where a variety of users share their thoughts that include both technical and pedagogical information. If it's not done together, one stakeholder is going to be chosen over the other, which makes the entire approach less effective.

Finally, respondents said that improving LLM integration should not be limited to grading. It should also be used to boost other parts of teaching, like as adaptive content development, multilingual feedback, real-time diagnostics, and more. While prior research often identifies scalability as the primary benefit of AI, this study demonstrates that scalability, in the absence of contextual adaptation, may result in superficial implementation. The requirement for culturally responsive, inclusive tools is similar (Zubairi et al., 2021) call for: equity-oriented EdTech. However, there is a conflict: the fast pace of AI integration needs to be balanced with the need to pay attention to pedagogy and infrastructure problems in India. The following phase would be to make Moodle-LLM structures that are as efficient as possible while remaining sure that everyone can use them. This way, integration will improve fairness rather than making existing unfairness worse.

Chapter VI:

Summary, Implications, and Recommendations

## 6.1 Summary

This research study has investigated the possibility of introducing the AI-driven Large Language Models (LLMs) into Moodle-based tests in the Indian EdTech market. Stakeholders are happy with the outcomes, both in terms of the positive impacts of LLMs and their limits. A few differences based on user positions, previous work with Moodle, and classroom exposure, but a statistical test showed that the difference was not important. Rather, the willingness to adopt LLM was more influenced by the daily pedagogical issues (delays in grading and workload-related pressures), indicating that the factors that lead to interest in AI-enabled services were pragmatic bottlenecks related to everyday work rather than professional levels.

Combinations of the outcomes answer the three guiding research questions in a nuanced way. In the case of RQ1, the evidence demonstrates that the value of LLM is mostly based on the ability to enhance the consistency of grades, efficacy, and time, but issues with bias and ethical considerations still persist. In regard to RQ2, the stakeholders emphasised that no personalisation can occur without localisation, particularly in the forms of regional language support, affordability, and culturally-minded content, as it is the India-based diverse education ecosystem. Finally, and in consideration of RQ3, the study has demonstrated that optimisation of the integration of LLM must not be dependent on the technical expertise of Moodle, but instead a balance of mobile accessibility, teacher training and scalability through the establishment of stakeholder collaboration.

These three aspects are considered jointly in this study, explaining why the effectiveness of an LLM-based assessment in India will hinge not only on the novelty of the technology but also on the extent to which the technology is sensitive to context, fair, and flexible to various learning contexts. This integrative knowledge forms a background to developing AI-enabled assessment systems, which are not only effective but also inclusive and pedagogically relevant in Indian classrooms.

## 6.2 Implications

The results of the investigation have significant implications for deploying AI-powered by LLM in Moodle-based evaluation systems within the Indian EdTech market. To begin with, the findings emphasise the need to learn more about how user roles can shape perceptions of AI efficacy. Developers, administrators, and teachers have different expectations, but all of them see a good reason to use AI, as it can greatly enhance the speed and consistency of feedback. Such insights suggest that optimal AI implementation should be tailored to specific roles and developed to cater to a diverse audience. Developers and institutions should collaborate to ensure that tools are utilised to address context-specific pedagogical issues, particularly in resource-limited settings. It can lighten grade burdens and promote leaner, more flexible, and student-focused educational systems in the diverse academic institutions present in India by designing their tools to meet the needs of all stakeholders.

Second, the close relationship between the features of personalisation and the need to tailor local content highlights the twofold need for both adaptable and culturally appropriate AI tools. Although differentiated learning can be achieved through social media personalisation using LLMs, it can only be realised in combination with content that is linguistically, culturally, and curriculum-wise differentiated. This is especially important in India, where students come from diverse languages, regions, and socio-economic backgrounds. The many context-aware AI functions can be added to Moodle using its modular structure, combined with the plugin ecosystem, providing a versatile framework through which to roll out at scale. When people like developers and politicians make choices and create things, they should change these tools to value cultural understanding more than just how well they work. This helps build fair and welcoming learning environments that work well in the unique Indian education system.

Third, there is a weak connection between having used Moodle before LLM and how useful the LLM is seen to be. This suggests that it is a key part when it comes to digital readiness and building skills. Just knowing how to use Moodle won't help you use AI unless you have good answers to the real problems teachers face, like not having enough time or other ways to assess students. This observation indicates that technical training alone is inadequate. Instead, implementation techniques should focus on the value they are, how well they fit into an existing process, and how relevant they are. The professional growth sessions must involve practical experience with the LLM-enhanced tools and highlight their role in alleviating regular teaching responsibilities. This observation indicates that technical training alone is inadequate. Instead, implementation techniques should focus on the value they are, how well they fit into an existing process, and how relevant they are. The professional growth sessions must involve practical experience with the LLM-enhanced tools and highlight their role in alleviating regular teaching responsibilities.

Finally, this study's concluding implication is that design should be collaborative and open to all participants. Stakeholders brought up numerous aspects of using AI, like making it available on smartphones and tablets, helping teachers, and using plugins. This shows that a good AI-in-Moodle strategy can't be one-dimensional. Instead, institutions should design a collaborative methodology involving input from educators, students, developers, and policymakers to collaboratively create LLM-based solutions that are both technologically sound and pedagogically beneficial. This applies more widely to the future of EdTech in India: LLM integration should no longer be only about automation; it should also be about smart systems that can adapt to the user's context, language variety, and the realities of the infrastructure. These consequences point out the necessity to create AI tools not merely as developments in technology but also as holistic educational tools to address the dynamic and varied digital learning requirements of India.

## 6.3 Recommendations for Future Research

Based on the findings of the current study, some recommendations for additional steps are proposed. These suggestions are given ratings in order of how crucial and possible they are in the Indian EdTech setting.

**Immediate Priorities:**

Future research and work should focus on developing and testing locally adapted LLCM that considers the linguistic, infrastructural, and curriculum differences across India. These studies should compare how well these region-specific AI tools work against standard global models. Experiments should take place in various education systems, including rural and urban schools, government-run institutions, and privately owned education systems. Also, people will need to talk about how AI evaluations affect fairness and inclusion. The research should be shared with important groups of students, like those from rural areas, non-English speakers, and students with disabilities, to find out if the assessments done by a large language model can help create a fairer education system. Lastly, ethical and policy guidelines will be developed, and this is very important. The researchers need to talk about how to manage AI in education and find ways to deal with problems like transparency, data privacy, biased algorithms, and holding people accountable. Studies focused on policies can help make rules and laws that encourage the fair, equal, and inclusive use of large language models in education assessments in India.

### Medium-Term Research Directions

The role-based qualitative inquiry should be subjected to research in the medium term, to complete the quantitative results of the current study. Interviewing or focus grouping teachers, administrators and developers will offer more insight on the variation in the perceptions of the integration of LLMs into Moodle. This type of qualitative research will assist in unravelling of contextual issues, challenges and expectations that can not be fully reflected in survey data. Moreover, technical reliability and evaluation systems validation depends on the application of the LLM. Regular test-retest of human scoring versus AI-based scoring should be conducted to assess accuracy, fairness and error rates to establish credibility in automated grades. The other important area of research that ought to be undertaken in the medium term is mobile usability and infrastructure studies. Because mobile devices are ubiquitous, and commonly used in India, more research is required to determine the extent to which the LLM-based tools can work in low-bandwidth or resource-constrained settings to enable the AI-based assessment to be viable, available, and practical in a broad spectrum of educational institutions.

### Long-Term Research Opportunities

The long-term research should be directed to estimating the long-term efficacy of the evaluation systems according to LLM compared with the different elements of the educational ecosystem. In particular, longitudinal research would be needed to identify effects on teacher autonomy, workload management, grading equity, and student learning performance in general, which will be used to uncover how AI integration can promote teaching practices and student learning conditions in the long term. In addition, platform comparative analysis can offer valuable information on the comparative strengths and limitations of different LMS sites, e.g., Moodle, Google Classroom, Canvas, or Blackboard, in helping to integrate LLMs and AI-assessment systems. Finally, but not the least, the hybrid human/AI evaluation systems should be considered since these systems will encompass automated grading and human oversight. Studies are needed to determine the efficiency and fairness of such hybrid solutions and how such solutions can be more or less effective relative to the contextual conditions, learning context, or the nature of assessment tasks, which can guide effective practices in balanced and adaptive AI-assisted evaluation.

Ultimately, the next phase of the investigation must extend beyond proof-of-concept to assess the long-term, comprehensive, and ethical viability of LLM-based evaluation systems. Future research can ensure that AI has a significant impact on the diverse and evolving Indian educational landscape by focusing on localised adaptation, equity issues, and governance frameworks.

## 6.4 Conclusion

This study explored the potential to apply Large Language Models (LLMs) in Moodle-based assessment in the Indian EdTech scenario. It gives empirical and theoretical data on the ways AI can reshape the evaluation practices in various learning institutions by responding to three research queries.

The results show that even though people have different views on how effective LLMs are based on their role, most agree that they make grading more consistent, timely, and scalable. Educators who had the biggest role in grading were the most positive about LLMs, which shows that the real value of AI is clear when it helps solve actual problems in teaching. This goes beyond just talking about whether to use AI, and makes LLMs look like a good solution for the big challenges in education.

At the same time, the study also shows that personalisation can't work well without a good understanding of the context. The positive relationship between adaptive features, user interest, and local content needs shows why AI systems need to be culturally smart and include different languages. By showing this link, the research helps build the theory behind adaptive AI in education, which is usually not discussed enough in global EdTech conversations.

Another significant thing it does is challenge ideas about how familiar people are with technology. The views towards the integration of the LLM were not significantly affected by previous exposure to Moodle, suggesting that the success of the implementation depends on the alignment of AI tools with pedagogical procedures, the characteristics of the infrastructure, and teacher training. This information shifts the focus of future EdTech design from ecosystem-based plans that have many stakeholders to platform-centred designs.

The findings do substantiate the debate about the role of AI in education, theoretically and practically. They are added to the discussion of AI use testing through analysing the role of AI in the social and language context in India. Practically, they point out the necessity to create solutions that are affordable, user-friendly, useful among teachers, as well as, encouraging innovativeness and equity.

Concisely, the introduction of a large language model into Moodle might transform the approach to administering tests in an Indian classroom, however, this will not be effective until the introduction is perceived as a technological enhancement or a cultural more conscious educational modification. When properly implemented, with concerns of scalability, fairness, local adaptation, and teamwork, AI-based assessment can become a means of educational justice, helping the EdTech industry in India develop a livelier, student-centred future.

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Appendix A:

Dataset

| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Your Role | Organization | Have you per | What do you : | How effective | What is the m | How consiste | What types of | How effective | What LLM fea | What would n | How importar |
| 2 | 1 | 2 | 1 | 2 | 2 | 3 | 2 | 3 | 2 | 3 | 2 | 2 |
| 3 | 2 | 2 | 1 | 2 | 4 | 2 | 3 | 3 | 1 | 3 | 1 | 4 |
| 4 | 5 | 2 | 1 | 2 | 5 | 2 | 3 | 2 | 2 | 2 | 1 | 2 |
| 5 | 4 | 3 | 1 | 1 | 5 | 2 | 5 | 4 | 1 | 2 | 1 | 4 |
| 6 | 4 | 4 | 1 | 2 | 5 | 3 | 4 | 3 | 3 | 2 | 2 | 3 |
| 7 | 2 | 2 | 1 | 2 | 5 | 2 | 4 | 3 | 3 | 1 | 3 | 4 |
| 8 | 3 | 2 | 1 | 2 | 5 | 2 | 4 | 3 | 3 | 2 | 4 | 4 |
| 9 | 5 | 2 | 1 | 3 | 4 | 3 | 5 | 4 | 3 | 2 | 1 | 4 |
| 10 | 4 | 2 | 1 | 4 | 2 | 3 | 4 | 1 | 3 | 1 | 4 | 4 |
| 11 | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 4 | 2 | 3 | 1 | 4 |
| 12 | 1 | 3 | 1 | 1 | 1 | 2 | 4 | 2 | 3 | 2 | 1 | 3 |
| 13 | 4 | 3 | 1 | 3 | 5 | 3 | 4 | 3 | 2 | 1 | 3 | 2 |
| 14 | 1 | 2 | 1 | 3 | 4 | 2 | 3 | 3 | 2 | 3 | 1 | 3 |
| 15 | 1 | 2 | 1 | 3 | 3 | 2 | 3 | 4 | 1 | 2 | 3 | 3 |
| 16 | 1 | 2 | 1 | 2 | 3 | 2 | 3 | 3 | 3 | 3 | 1 | 3 |
| 17 | 1 | 2 | 1 | 1 | 4 | 2 | 4 | 3 | 2 | 2 | 3 | 4 |
| 18 | 1 | 2 | 1 | 3 | 4 | 3 | 4 | 3 | 2 | 2 | 3 | 3 |
| 19 | 1 | 2 | 1 | 1 | 5 | 2 | 4 | 3 | 3 | 2 | 2 | 4 |
| 20 | 1 | 2 | 1 | 2 | 4 | 2 | 4 | 4 | 2 | 2 | 2 | 3 |
| 21 | 1 | 2 | 1 | 2 | 3 | 2 | 4 | 3 | 3 | 3 | 2 | 4 |
| 22 | 1 | 2 | 1 | 2 | 3 | 2 | 4 | 2 | 3 | 4 | 3 | 4 |
| 23 | 5 | 4 | 1 | 2 | 3 | 3 | 4 | 2 | 3 | 2 | 3 | 4 |
| 24 | 3 | 2 | 1 | 2 | 4 | 2 | 2 | 2 | 3 | 2 | 3 | 4 |
| 25 | 1 | 2 | 1 | 2 | 4 | 2 | 3 | 1 | 2 | 2 | 2 | 2 |
| 26 | 1 | 2 | 1 | 2 | 4 | 2 | 4 | 2 | 2 | 2 | 2 | 4 |
| 27 | 4 | 2 | 1 | 1 | 4 | 2 | 2 | 2 | 2 | 4 | 2 | 3 |
| 28 | 3 | 2 | 1 | 3 | 4 | 2 | 1 | 1 | 1 | 1 | 1 | 1 |
| 29 | 4 | 2 | 1 | 3 | 2 | 1 | 2 | 2 | 2 | 2 | 1 | 1 |

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | **Which Moodle AI tools have** | **Which plugins below suppor** | **What challenges do you face** | **Please describe any strengt** | **What is the most significant** | **What features or improvements would make AI evaluation tools more useful in your institution? *(E.g., multilingual feedba*** |
| 2 | OpenAI Question Generator | Compilation Plagiarism Detect | Moodle’s AI plugins face challe | LLM-based tools offer fast, per | Enabling real-time student ana | Multilingual feedback, customizable rubrics, offline access, improved accuracy, real-time analytics, teacher dashboards, bias reduction, and seamless |
| 3 | Adaptive Quiz Plugin, AI Feedb | AI Connector | Challenges include limited cust | LLM-based evaluation tools off | Enabling real-time student ana | Useful improvements include multilingual feedback, offline access, enhanced teacher dashboards, customizable rubrics, better integration with LMS, |
| 4 | OpenAI Question Generator, A | OpenAI Question Generator | Sometimes the AI gives inaccu | LLM tools are fast and reduce | Enabling real-time student ana | Multilingual feedback support would help our diverse student body feel more included and understood during assessments. |
| 5 | OpenAI Question Generator, C | OpenAI Question Generator | Integration with existing Mooc | Feedback is instant and helps s | Enabling real-time student ana | A real-time teacher dashboard showing student performance trends would improve intervention and instructional planning. |
| 6 | AI Feedback Generator | AI Connector | The AI plugin struggles to unde | It streamlines evaluation with | Automating grading and feedb | Offline capabilities are essential for rural areas with unreliable internet access. |
| 7 | Adaptive Quiz Plugin | OpenAI Question Generator | Privacy concerns are significan | Speeds up grading significantly | Delivering adaptive learning e | Customizable rubrics to align AI grading with our institution’s specific assessment policies. |
| 8 | Adaptive Quiz Plugin, AI Feedb | All of the above | Customization options are too | The automatic feedback is stru | Enabling real-time student ana | Ability to adjust grading weights for specific components in different assignment types. |
| 9 | OpenAI Question Generator, A | OpenAI Question Generator | It doesn't support all file types | LLMs handle factual answers w | Enabling real-time student ana | Ability to adjust grading weights for specific components in different assignment types. |
| 10 | AI Feedback Generator, Custo | AI Connector | Language support is poor for n | Language support is poor for n | Delivering adaptive learning e | Cross-platform compatibility, especially for mobile and tablet-based learning environments. |
| 11 | Custom AI Plugins | OpenAI Question Generator | The AI tends to overemphasize | We appreciate the quick turna | Supporting multilingual conter | A visual analytics dashboard to monitor grading patterns and anomalies. |
| 12 | Turnitin (Plagiarism Detection) | All of the above | The plugin’s documentation is | The personalization in feedbac | Delivering adaptive learning e | Cross-platform compatibility, especially for mobile and tablet-based learning environments. |
| 13 | OpenAI Question Generator | Compilation Plagiarism Detect | AI evaluation results often req | Speed and efficiency are excell | Delivering adaptive learning e | More contextual understanding in feedback rather than keyword-based responses. |
| 14 | Adaptive Quiz Plugin | OpenAI Question Generator | Delayed processing times durir | Scales easily across classes, but | Delivering adaptive learning e | Better support for diagrams, coding languages, and non-text responses. |
| 15 | OpenAI Question Generator | AI Connector | It’s hard to trust the fairness o | The automated rubric alignme | Enabling real-time student ana | Inclusion of culturally sensitive evaluation patterns to avoid bias. |
| 16 | Adaptive Quiz Plugin | OpenAI Question Generator | AI tools sometimes fail to unde | Works efficiently for high-volur | Enabling real-time student ana | Adaptive learning suggestions after evaluation to guide students on what to study next. |
| 17 | OpenAI Question Generator, A | All of the above | The plugin isn’t fully compatibl | Great for basic comprehensior | Enabling real-time student ana | Adaptive learning suggestions after evaluation to guide students on what to study next. |
| 18 | AI Feedback Generator | All of the above | Compatibility with other Mooc | Saves effort for large batches, | Enabling real-time student ana | Role-based access control for admins, teachers, and students. |
| 19 | Adaptive Quiz Plugin | OpenAI Question Generator | It doesn’t allow collaborative e | Personalization works better ir | Delivering adaptive learning e | Annotations or inline feedback options for detailed assessment reviews. |
| 20 | Adaptive Quiz Plugin | OpenAI Question Generator | Bias in AI evaluations sometim | It reduces evaluator fatigue, b | Enabling real-time student ana | Greater flexibility in assessment formats supported (e.g., case studies, projects, group work). |
| 21 | Adaptive Quiz Plugin | OpenAI Question Generator | Feedback generation doesn’t a | Immediate results help manag | Enabling real-time student ana | AI tutor suggestions alongside grades to support weak areas. |
| 22 | Adaptive Quiz Plugin | OpenAI Question Generator | It’s difficult to override AI scor | AI grading improves turnarour | Enabling real-time student ana | Student-friendly feedback summaries for easy comprehension. |
| 23 | Adaptive Quiz Plugin | AI Connector | Difficulty in setting AI criteria t | Personalized tips are apprecia | Delivering adaptive learning e | Team grading support where AI can assist multiple evaluators simultaneously. |
| 24 | Adaptive Quiz Plugin | Compilation Plagiarism Detect | Difficulty in maintaining acade | Clear rubric-based evaluation I | Enabling real-time student ana | Visual score breakdowns by skill areas to show strengths and weaknesses. |
| 25 | Adaptive Quiz Plugin | AI Connector | It’s hard to explain AI-driven g | Reduces admin time, though t | Enabling real-time student ana | Accessibility features like screen reader compatibility and contrast adjustments. |
| 26 | OpenAI Question Generator, A | OpenAI Question Generator | Difficulty in setting AI criteria t | Helpful for formative assessme | Supporting multilingual conter | Predictive analytics to forecast student risk based on AI evaluation trends. |
| 27 | OpenAI Question Generator | Compilation Plagiarism Detect | The plugin takes up too much s | Standardized feedback helps st | Enabling real-time student ana | Integration with external tools like Turnitin or Grammarly. |
| 28 | Adaptive Quiz Plugin | AI Connector, All of the above | It sometimes marks correct an | Personalized tips are apprecia | Supporting multilingual conter | Student dashboards showing AI-generated learning recommendations. |
| 29 | OpenAI Question Generator | AI Connector | Student dashboards showing A | Students benefit from instant f | Enabling real-time student ana | Drag-and-drop rubric builders for ease of customization. |
| 30 | Turnitin (Plagiarism Detection) | Compilation Plagiarism Detect | Moodle updates often break tl | Excellent speed and structure, | Automating grading and feedb | Data privacy and compliance features for institutional and regional standards. |
| 31 | Adaptive Quiz Plugin | Compilation Plagiarism Detect | Moodle updates often break tl | Reduces workload dramaticall | Enabling real-time student ana | Support for competency-based assessment methods. |