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Leveraging Moodle for Personalised E-Learning: A Framework-Based Analysis of Tools, Resources and Plugins

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Abstract

This exploratory study examines the feasibility of Moodle as a platform for personalised e-learning, emphasizing resources, tools, and plugins that facilitate instructional adaptation according to diverse learner characteristics. The research relates these Moodle features with the Personalised Learning Design Framework (PLDF) proposed by Short (2022), which delineates essential elements for individualised learning. The PLDF specifically covers five essential aspects: Instructional Elements, Dimensions of Personalised Learning, the entity responsible for customizing instruction, the level of learner agency in this process, and the types of data that inform instructional adaptations. A framework-based qualitative analysis was conducted on a curated set of Moodle activities and plugins selected from the Moodle plugin repository and core LMS features. Each was systematically mapped against the five PLDF components to assess its personalisation potential. The findings reveal that tools such as Lesson, and Conditional Activities support adaptive content delivery and differentiated assessments. Plugins like Adaptive Quiz and H5P interactive elements enable data-informed personalisation, while features such as User Overrides and Groupings facilitate instructor-driven customisation. These results highlight Moodle's capacity to support various dimensions of personalised learning and delivers an exhaustive reference for educational technologists and LMS specialists, presenting practical insights into the optimal utilisation of Moodle's features to enhance personalised learning experiences – enabling more inclusive and learner-centreed educational environments. This paper establishes a basis for the actual execution of personalised learning activities, assisting instructors in customizing instruction to enhance engagement and outcomes for all students.

Keywords: Personalised learning, Adaptive learning, Moodle, PLDF framework, e-Learning
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Introduction

The shift from the industrial age to a knowledge-driven, information-based society has redefined the desired outcomes of education. In this context, education systems are demanding individuals who are innovative, collaborative, and skilled in problem-solving. These evolving expectations have given rise to the concept of tailored education, encompassing approaches of personalised learning. Personalised and adaptive learning are reshaping higher education by shifting the focus from instructor-centreed pedagogies to student-centreed pedagogies. The history of personalised learning demonstrates that students tend to learn more effectively when instruction is tailored to their individual learning needs where new pedagogy of personalisation recognises that each student is different (Taylor, Yeung, & Bashet, 2021). Personalised learning refers to a pedagogical approach in which the pace of learning, instructional preferences and the learning content are optimised to suit the needs of each learner (Raj & Renumol, 2022). In the latter half of the 20th century, personalised learning emerged in digital form through intelligent tutoring systems. In today's 21st century learning paradigm, big data and learning analytics are transforming the potential of personalised learning by enabling systems to track, analyse, and respond to learners' needs in real time (Shemshack & Spector, 2020).

The adaptive e-learning environment (ALE) is an emerging research field focused on personalizing the digital learning experience. ALEs deal with the development approach by adjusting content delivery within learning management systems (LMS) to fulfil students' learning preferences thereby transforming how e-content is delivered (Normadhi, et al., 2019). In an e-learning environment, standardised content often fails to meet diverse academic needs, especially where learners and instructors are geographically distant. Adaptive learning environments address this gap by tailoring content to the unique learning preferences of e-learners, thereby enhancing the effectiveness and quality of online education (El-Sabagh, 2021). Despite the future-oriented potential of adaptive e-learning, current educational practices remain largely centreed on traditional group-based instruction in classrooms (Burak & Gultekin, 2022), highlighting the need for broader adoption of adaptive learning technologies.

Despite its pedagogical appeal, the practical implementation of such environments remains fraught with complexity. As Pelánek (2024) notes, the development of adaptive systems involves intricate modeling challenges, trade-offs between automation and human oversight, and nuanced design decisions that are often underrepresented in mainstream literature. A central challenge lies in the lack of clarity surrounding the optimal strategies for designing and operationalizing adaptive personalised learning environments. Questions persist regarding the balance between learner agency and system-driven customisation, the granularity of data required for meaningful adaptation, and the pedagogical coherence of algorithmically generated learning paths (Barrera Castro et al., 2025). These uncertainties underscore the need for robust frameworks that guide the integration of adaptive features into instructional design.

As digital learning environments expand, Learning Management Systems (LMSs) like Moodle provide a critical infrastructure for implementing personalised learning on a scale. The architecture of a robust LMS supports customisation which allows for tailored learning paths that can adapt to individual student needs, performance, and learning preferences. However, the effectiveness of an LMS in supporting personalisation is contingent upon its technical capabilities, scalability, and alignment with pedagogical goals. Therefore, before deploying adaptive personalised learning environments, it is imperative to evaluate the feasibility and capability of the chosen LMS. A poorly matched system may hinder instructional innovation, limit scalability, or fail to support the nuanced requirements of adaptive learning (Gutierrez, 2022).

Moodle, an open-source LMS, is widely adopted across educational institutions and offers extensive functionalities that can be leveraged for instructional personalisation. While numerous studies have explored the capabilities of LMSs in facilitating online learning, fewer have focused on systematically analyzing these tools through the lens of personalisation frameworks. Evaluation frameworks that assess LMS features, integration potential, and user experience are essential for informed decision-making (Abid et al., 2024). Such assessments ensure that the LMS can accommodate evolving instructional needs, support diverse learner populations, and sustain long-term educational objectives. This study contributes to this discourse by examining Moodle's personalisation potential through the lens of the Personalised Learning Design Framework (PLDF), explore the extent to which Moodle features align with the components of PLDF, thus evaluating Moodle's potential as a platform for delivering personalised e-learning.

Review of Literature

Personalised and Adaptive Learning

Personalised and adaptive learning represents a paradigm shift in education, emphasizing the tailoring of instructional experiences to meet individual learner needs, preferences, and progress. Personalised learning focuses on aligning content, pacing, and assessment with each learner's unique profile, while adaptive learning leverages technology—particularly artificial intelligence and data analytics—to dynamically adjust instruction based on real-time learner performance.

Peng, Ma, and Spector (2019) define personalised adaptive learning as a technology-enabled pedagogy that continuously adjusts teaching strategies based on learners' evolving characteristics and performance. This approach integrates smart learning environments to support flexible, responsive instruction that evolves with learner progress. Adaptive learning systems, as described by Taylor, Yeung, and Bashet (2021), personalise instruction by evaluating student performance and generating individualised learning pathways through artificial intelligence and machine learning. These systems aim to enhance learner satisfaction and achievement by offering differentiated content, pacing, and feedback. Mirari (2022) conducted a meta-analysis of 25 studies and found that individualised learning strategies significantly improve academic performance, engagement, and motivation across educational levels. The review underscores the importance of aligning instructional design with learner profiles and competencies to maximise personalisation outcomes.

The theoretical foundations of personalised and adaptive learning are rooted in constructivist and mastery learning paradigms, which advocate for differentiated instruction, formative assessment, and continuous feedback. Bloom's (1984) mastery learning model emphasised the potential for all students to achieve high levels of understanding when provided with appropriate instructional conditions and timely feedback. Similarly, Vygotsky's (1978) sociocultural theory introduced the concept of the Zone of Proximal Development (ZPD), highlighting the importance of scaffolding and collaborative learning in fostering cognitive growth.

Contemporary frameworks such as the Personalised Learning Design Framework (PLDF) proposed by Short (2022) and Universal Design for Learning (UDL) developed by CAST (2018) offer structured models for implementing personalisation across instructional elements, learner agency, and data-informed decision-making. PLDF identifies five key components—Instructional Elements, Personalisation Dimensions, Who Customises, Learner Agency, and Data Used—providing a comprehensive lens for evaluating and designing personalised learning systems. UDL, on the other hand, emphasises multiple means of engagement, representation, and expression to ensure accessibility and inclusivity in learning environments. These frameworks underscore the importance of aligning pedagogical strategies with technological capabilities to support meaningful, equitable, and learner-cantered educational experiences.

The growing body of literature underscores the transformative potential of personalised and adaptive learning in creating inclusive, efficient, and engaging educational experiences (Katiyar et al., 2024; Raj & Renumol, 2024). As educational institutions increasingly adopt digital platforms, the integration of these approaches becomes essential for fostering meaningful and equitable learning pathways. Empirical studies have demonstrated the effectiveness of personalised and adaptive learning environments in improving academic outcomes, learner satisfaction, and retention rates. For instance, Sayapina et al. (2024) found that adaptive feedback mechanisms significantly enhanced student engagement, while Raj and Renumol (2021) reported improved performance among learners exposed to AI-driven instructional pathways. Personalised Learning Paths (PLPs), informed by prior performance and learning preferences, have been shown to optimise instructional delivery and foster deeper understanding (Nicolaidou & Nicolaidou, 2024; Shemshack & Spector, 2020).

Despite these promising developments, challenges remain in the practical implementation of adaptive personalised learning. Concerns include the ethical use of learner data, algorithmic transparency, and the pedagogical coherence of automated systems (Pelánek, 2024; Fadieieva, 2021). Moreover, there is limited clarity in the literature regarding best practices for designing and executing adaptive learning environments, particularly within existing digital infrastructures. This gap highlights the need for systematic evaluations of learning platforms to determine their feasibility and alignment with personalisation frameworks—an area this study seeks to address.

The Role of LMS in Enabling Personalised Adaptive Learning

The integration of Learning Management Systems (LMS) with personalised adaptive learning (PAL) has become a cornerstone of modern e-learning environments. PAL leverages technology—particularly artificial intelligence and real-time analytics—to tailor learning experiences based on individual learner needs, preferences, and progress (Peng et al., 2019; Zhang et al., 2023). This dynamic approach contrasts with traditional static models, offering learners customised pathways that enhance engagement, retention, and equity in learning outcomes (Katiyar et al., 2024; Khomo et al., 2025).

Smart Learning Environments (SLEs) that incorporate PAL features demonstrate the transformative potential of LMS platforms. By synthesizing adaptive methods with conventional LMS structures, these systems enable personalised learning paths (PLPs) that adjust pacing, instructional strategies, and assessments according to learner profiles (Nicolaidou & Nicolaidou, 2022; Komleva & Vilyavin, 2020). Inputs such as prior performance and learning style preferences inform content delivery, fostering deeper understanding and learner satisfaction (Shemshack & Spector, 2020; Raj & Renumol, 2021).

A robust LMS architecture supports modularity and interoperability, allowing seamless integration with educational resources and analytics tools. This facilitates data-driven insights into learner engagement and progress, empowering educators to refine instructional strategies in real time (Budhner et al., 2024). Moreover, LMS platforms accommodate diverse content formats—text, video, interactive modules—catering to varied learning preferences and promoting motivation (Thakre, 2024; Amelia & Suranto, 2025).

Central to adaptive learning within LMS is the use of AI-driven feedback mechanisms. These systems analyse learner behaviour and performance to deliver immediate, personalised feedback and content adjustments (Ikhsan et al., 2024). This enables a shift from passive information consumption to active, self-paced learning experiences, enhancing mastery of complex concepts and overall learner efficacy (Munna et al., 2024). LMS platforms are not merely administrative tools but strategic enablers of personalised adaptive learning. Their capacity to support customisation, data analytics, and multimodal content delivery positions them as essential infrastructures for inclusive and learner-centreed e-learning environments.

Moodle as a Learning Management System in e-Learning

Moodle (Modular Object-Oriented Dynamic Learning Environment) has established itself as a leading learning management system (LMS) in global e-learning contexts, largely due to its open-source architecture and adaptability across diverse educational settings. As institutions increasingly adopt digital platforms to support flexible and engaging learning environments, Moodle offers a robust framework for implementing both fully online and blended learning modalities. Its modular design enables educators to incorporate multimedia resources, interactive activities, and differentiated instructional strategies, thereby enhancing pedagogical effectiveness and accommodating varied learning styles (Hizam et al., 2021; Wiyono et al., 2020).

One of Moodle's key strengths lies in its ability to transcend traditional constraints of time and space, fostering real-time interaction between learners and instructors. This capability supports synchronous and asynchronous communication, which has been shown to improve learner engagement and satisfaction (Partarakis & Zabulis, 2023; Ma et al., 2020). Moreover, Moodle's accessibility and low-cost implementation make it particularly valuable in socio-economically challenged contexts. Studies indicate that its functionality can support quality online education without requiring substantial financial investment, thereby expanding access to digital learning opportunities in underserved regions (Utami et al., 2021).

Moodle's versatility extends to its support for a wide array of teaching methodologies and digital learning objects, including forums, workshops, quizzes, and collaborative tools (Flores-Piñas et al., 2022; Febliza & Okatariani, 2020). Its adaptability allows institutions to tailor course structures to meet specific pedagogical goals, making it a preferred LMS for enhancing distance learning initiatives (Gamage et al., 2022). The platform's emphasis on interaction and collaboration aligns with contemporary educational theories that prioritise active learning and peer engagement as drivers of academic success (Satriani et al., 2021).

In blended learning environments, Moodle provides a cohesive framework that integrates online and face-to-face components, enriching the overall learning experience. Its support for synchronous and asynchronous activities enables instructors to design flexible, learner-centreed courses that respond to diverse student needs and preferences (Nasrum, Subawo, & Hidayati, 2023; Wati et al., 2023). The incorporation of multimedia content, interactive assessments, and discussion forums contributes to sustained learner motivation and engagement—critical factors for success in digital education (Simamora et al., 2022).

Personalised Learning Design Framework (PLDF)

The Personalised Learning Design Framework (PLDF), proposed by Short (2022), offers a comprehensive structure for conceptualizing and implementing personalised instruction in digital learning environments. It delineates five interrelated components that guide the design of adaptive learning experiences. Together, these components provide a robust framework for evaluating and designing personalised learning systems, ensuring that instructional strategies are both learner-centreed and data-informed.

1. Instructional Elements: Components of instruction that can be adapted (e.g., content, tasks, feedback).
2. Personalisation Dimensions: Aspects of learning that can be tailored (e.g., pace, goals, content).
3. Who Customises: The agent responsible for personalisation (e.g., instructor, learner, or system).
4. Learner Agency: The degree of control and autonomy the learner has in the personalisation process.
5. Data Used: The types of data used to inform personalisation (e.g., preferences, performance, behaviour).

Methodology

Research Design

This study adopted a qualitative exploratory design using a framework-based content analysis approach (Gale et al., 2013; Hassan, 2024). The Personalised Learning Design Framework (PLDF) served as the analytical lens through which Moodle's core features and selected plugins were evaluated. This approach enabled a structured and theory-driven mapping of LMS capabilities to personalisation elements Klingberg et al. (2024), allowing for systematic interpretation beyond descriptive comparison.

Selection of Moodle Tools and Plugins

Moodle version 4.1 (LTS) was selected as the base platform for analysis due to its widespread adoption in academic institutions and its stable feature set. To ensure methodological rigor, the selection of

Moodle tools and plugins followed a purposive sampling strategy grounded in predefined inclusion criteria as below:

- Tools were required to demonstrate explicit relevance to personalised learning, particularly in enabling adaptation of content, pacing, feedback, or learner pathways.
- Only tools with sustained community validation that are evidenced by high user ratings (≥4 stars), active maintenance, and recent updates were included to ensure reliability and contemporary relevance.
- Tools had to be applicable across diverse instructional contexts (e.g., formative assessment, content delivery, learner interaction), ensuring transferability of findings.
- Alignment with at least one PLDF component was required as a theoretical anchor.

The selection process involved an initial screening of Moodle core features and plugins from the official Moodle Plugin Directory, followed by iterative filtering based on the criteria above. This resulted in a final sample of 12 tools and features, comprising both core functionalities (e.g., Conditional Activities, Lesson, Grouping) and selected plugins (e.g., Adaptive Quiz, Personalised Learning Designer, Level Up!).

Operationalisation of PLDF Components

To ensure analytical consistency and methodological transparency in the framework-based mapping, each component of the Personalised Learning Design Framework (PLDF) was operationalised using explicit, theory-informed analytical indicators derived from Short (2022). These indicators guided the systematic evaluation of each Moodle tool or plugin against the five PLDF components.

Instructional Elements were identified by examining whether and how a tool enables modification of core instructional components, including content presentation, assessment structure, feedback mechanisms, learning tasks, or pacing conditions. *Personalisation* dimensions were categorised according to whether the tool supports adaptation in pace, path, goals, or content. The component *"Who Customises"* was determined by identifying the primary agent responsible for instructional adaptation within the tool's design: whether personalisation is driven by the instructor, the learner, or automated system logic.

Learner Agency was operationalised as a graded construct reflecting the extent of learner control within the personalisation process and classified into three levels: low, medium, and high, based on the degree of control afforded to learners. Low learner agency denotes system- or instructor-controlled environments in which learners follow predefined learning paths with minimal opportunity for choice or decision-making. Medium learner agency reflects guided interaction, where learners exercise limited control within instructor-defined structures, such as selecting options, pacing interactions, or navigating predefined branches. High learner agency indicates substantial learner involvement in shaping learning pathways, goals, or content selection.

Data Used was categorised based on the primary data sources informing personalisation processes, including learner performance data (e.g., quiz scores), behavioural interaction data (e.g., activity logs, engagement metrics), and learner preference data (e.g., self-reported choices or selections).
The classification of Moodle tools was guided by an analytical coding rubric aligned with the PLDF components (Table 1), enabling systematic and transparent mapping across instructional, pedagogical, and data-oriented dimensions. Each tool was systematically evaluated against the rubric to ensure consistency in mapping.

Table 1. Analytical rubric for mapping moodle tools to PLDF components

PLDF Component	**Analytical Indicator**	**Operational Definition**
Instructional Elements	☐ Content	Tool modifies or differentiates instructional content
	☐ Assessment	Tool adapts assessment format, difficulty, or sequencing
	☐ Feedback	Tool enables tailored or conditional feedback
	☐ Learning Tasks	Tool personalises activities or task structure
Personalisation Dimensions	☐ Pace	Tool adjusts timing or progression speed
	☐ Path	Tool enables differentiated learning pathways
	☐ Goals	Tool supports personalised goal setting or targeting
	☐ Content	Tool customises or differentiates learning materials
Who Customises	☐ Instructor	Adaptation configured and controlled by instructor
	☐ Learner	Learner actively selects learning options or paths
	☐ System	Adaptation driven by automated rules or logic
Learner Agency	☐ Low	Learner follows predefined paths with minimal choice
	☐ Medium	Learner makes limited choices within structured options
	☐ High	Learner substantially influences pathways or decisions
Data Used	☐ Performance Data	Assessment scores, completion status
	☐ Behavioural Data	Interaction logs, engagement metrics
	☐ Preference Data	Learner-selected options or expressed preferences

For example, H5P Interactive Content was categorised as supporting learner agency at a medium level because it allows learners to actively engage with interactive elements such as quizzes and branching scenarios, enabling limited control over learning progression. However, as the structure and pathways are primarily predefined by the instructor, full autonomy is not achieved, justifying its classification as medium rather than high.

Data Collection and Analysis

Data on each selected tool/plugin were collected from multiple sources including official Moodle documentation, plugin pages, demonstration instances, and community forums. Each selected tool or plugin was systematically analysed and mapped to the five components of PLDF:

- Instructional Elements: What aspects of instruction the tool modifies
- Personalisation Dimensions: Which personalisation strategies are supported
- Who Customises: Whether customisation is driven by instructors, learners, or system logic
- Learner Agency: The degree of autonomy and choice afforded to learners
- Data Used: Types of data leveraged (e.g., performance metrics, learner preferences, activity logs)

The mapping was organised into a matrix format to enable comparative analysis and identify patterns of alignment across tools.

Trustworthiness Measures

To enhance the trustworthiness of the analysis, methodological triangulation was employed through the use of diverse data sources. Additionally, validation was conducted with a panel of two educational technology experts. Their feedback was incorporated to refine the feature mapping and ensure clarity in alignment with the PLDF.

Results and Discussions

The analysis yielded a structured mapping of selected Moodle tools and plugins against the five components of the Personalised Learning Design Framework (PLDF). Table 2 presents a synthesis of how each tool aligns with specific PLDF dimensions.

Table 2. Mapping of Moodle tools and plugins to PLDF components

Moodle Tool/ Function/ Plugin	Instructional Elements	Personalisation Dimensions	Who Customises	Learner Agency	Data Used
Lesson	Content, Feedback, Pacing	Path, Content	Instructor	Medium	Performance, Responses
Conditional Activities	Pacing, Environment	Pace, Path	Instructor	Low	Activity Completion
H5P Interactive Content	Content, Tasks, Feedback	Content, Goals	Instructor	Medium	Behaviour, Interaction
Adaptive Quiz	Assessment, Feedback	Pace	System	Low	Performance
Restrict Access + Groupings	Environment, Content	Path, Group	Instructor	Low	Profile Data
Level Up!	Feedback, Motivation	Goals	System	High	Behaviour
Personalised Learning Designer (PLD)	Tasks, Feedback	Path, Content, Goals	System	Medium	Performance, Behaviour
Feedback Activity	Feedback, Goals	Goals	Instructor	High	Responses

Choice Activity	Task, Feedback	Goal, Content	Learner	High	Preferences
Quiz with Conditional Questions	Content, Assessment	Content, Pace	Instructor	Medium	Performance
Forum with Ratings	Feedback, Motivation	Goals, Engagement	Instructor	Medium	Peer Feedback, Ratings
User Overrides	Pacing	Pace	Instructor	None	Performance

The results demonstrate that Moodle's tools vary in terms of the personalisation dimensions they support. Tools like Lesson and PLD span multiple components, offering both instructor and system-driven customisation. Learner agency is strongest in tools like Choice and Level Up!, while Adaptive Quiz and Conditional Activities primarily offer system- and instructor-driven personalisation. Most tools rely on behavioural and performance data, with fewer incorporating learner preferences explicitly.

The findings from the framework-based analysis highlight Moodle's considerable capacity to support various dimensions of personalised learning as conceptualised by Short's (2022) Personalised Learning Design Framework (PLDF). This section critically interprets the results, reflecting on the alignment between Moodle functionalities and the five PLDF components.

Alignment with Instructional Elements and Dimensions of Personalisation

The framework-based analysis demonstrates that Moodle exhibits strong alignment with PLDF components related to instructional elements and dimensions of personalisation, particularly in its support for differentiated content delivery, assessment adaptation, and learner engagement. Tools such as Lesson, Quiz, Assignment, and Adaptive Quiz enable instructors to modify instructional content, feedback, and pacing, while interactive and collaborative tools such as H5P, Forum, and Choice enhance engagement through varied representational and participatory modalities. These affordances allow Moodle to operationalise personalisation primarily through content sequencing, pacing control, and formative assessment, confirming its versatility as a platform for differentiated instruction and supporting earlier findings on Moodle's pedagogical flexibility (Alammary et al., 2014).

However, when examined through the PLDF lens, these strengths also reveal an important limitation. Personalisation in Moodle is largely enacted as design-time differentiation rather than as continuous, learner-responsive adaptation. As indicated in Table 2, tools that support personalisation dimensions such as pace and path rely heavily on predefined instructor rules (e.g., Conditional Activities, Restrict Access) rather than dynamically evolving learner models. Consequently, Moodle's personalisation mechanisms tend to prioritise instructional efficiency and scalability over real-time responsiveness, positioning personalisation as an extension of instructional design decisions rather than as an emergent property of learner–system interaction.

Entity Responsible, Learner Agency, and Structural Patterns

Analysis of the "Who Customises" component reveals a pronounced instructor-centric orientation across Moodle's personalisation ecosystem. As shown in Table 2, the majority of tools place customisation authority either with instructors or with automated system logic, while relatively few afford learners direct control over learning trajectories. Tools such as User Overrides, Grouping, and Conditional Activities empower instructors to tailor pacing and access conditions, reinforcing instructional oversight but limiting learner participation in customisation decisions.

Learner-driven personalisation is present but unevenly distributed. Tools categorised as supporting high learner agency, such as Choice Activity, Feedback Activity, and Level Up!, enable learners to influence goals, participation, or self-monitoring processes. Yet these tools primarily facilitate decision-making at the interaction level rather than at the level of content sequencing or instructional strategy. By contrast, tools such as Lesson, H5P Interactive Content, and Quiz with Conditional Questions occupy a medium-agency position, allowing learners to exercise constrained choice within instructor-defined structures. This pattern suggests that Moodle conceptualises agency largely as guided engagement rather than as learner authorship of learning pathways.

This distribution reinforces critiques that contemporary LMS environments, including Moodle, privilege teacher-driven personalisation over learner-driven personalisation (Ifenthaler & Yau, 2020). From a PLDF perspective, Moodle demonstrates partial alignment with the learner agency component: while learners are encouraged to interact actively, they are rarely positioned as co-designers of their learning experience. The framework analysis thus reveals a structural asymmetry between instructional adaptability and learner empowerment within Moodle's design logic.

Data-Informed Personalisation and Its Limits

Moodle demonstrates robust alignment with the PLDF component related to data use, leveraging learner performance and behavioural data to inform instructional decisions. Tools such as Adaptive Quiz and the progress monitoring functions enable instructors and systems to monitor progress, identify learning gaps, and adjust instructional pacing accordingly. As highlighted in Table 2, performance and behavioural data dominate Moodle's personalisation processes, supporting formative assessment and instructor-led adaptation. This finding aligns with Berland et al.'s (2013) emphasis on the role of learning analytics in understanding learner pathways within adaptive systems.

However, the predominance of performance-centric data also constrains the scope of personalisation. Few tools incorporate learner preference data or metacognitive indicators that would support more holistic personalisation strategies. Consequently, data-informed personalisation in

Moodle tends to be reactive, responding to observed performance rather than anticipatory or preference-sensitive. This limits Moodle's capacity to support richer interpretations of learner needs as envisioned by PLDF, where personalisation is informed not only by what learners do, but also by what they prefer, value, or aim to achieve.

Trade-offs, Challenges, and Design Implications

Synthesizing these findings reveals a persistent trade-off between automation, learner agency, and pedagogical control. System-driven tools such as Adaptive Quiz and Personalised Learning Designer offer scalable, data-responsive personalisation but are associated with low learner agency, as decision-making authority remains embedded within algorithmic or instructor-defined rules. Conversely, tools that support higher learner agency privilege autonomy and engagement but lack automated adaptivity, placing greater responsibility on learners without corresponding system intelligence.

These tradeoffs expose a fundamental tension within Moodle's personalisation architecture: increasing automation centralises control within the system, while increasing agency decentralises personalisation but reduces responsiveness. From a PLDF standpoint, Moodle aligns strongly with instructional and data-oriented components but only partially addresses learner agency and autonomous system customisation. Moreover, while third-party plugins can extend adaptive functionality, their reliance on additional technical integration and administrative expertise raises questions about scalability and sustainability in institutional contexts.

Rather than framing these constraints as deficiencies, the PLDF analysis underscores the importance of intentional instructional design. Moodle's capacity to support personalised learning is not solely determined by its technical features, but by how educators orchestrate tools to balance automation, agency, and pedagogical coherence. In this sense, Moodle functions less as an autonomous adaptive system and more as a personalisation-enabling infrastructure, placing the onus on educators and designers to realise the full pedagogical potential of personalised e-learning.

Limitations and Future Directions

While this study offers a systematic, framework-based analysis of Moodle's personalisation affordances, several limitations must be acknowledged. First, the study adopts an exploratory qualitative design and relies primarily on secondary data sources, including documentation, demonstrated functionality, and expert validation. As such, the findings reflect the potential for personalisation embedded within Moodle's tools and plugins rather than their realised pedagogical impact in authentic learning contexts.

Consequently, conclusions should be interpreted as design-level insights rather than definitive claims about learning effectiveness.

Second, the analysis deliberately focused on a curated subset of Moodle tools and plugins, selected to represent diverse instructional, adaptive, and engagement-oriented functionalities. Although the selection was guided by explicit criteria and validated through expert review, it does not capture the full breadth of Moodle's plugin ecosystem or institution-specific customisations. Additionally, the framework-based mapping necessarily involved interpretive judgement, particularly in classifying constructs such as learner agency. While transparent rubric and expert validation were employed to enhance trustworthiness, alternative interpretations may emerge when tools are enacted differently across instructional contexts.

Third, the study does not include empirical learner-level data, such as student perceptions, engagement metrics, or learning outcomes. As a result, the analysis cannot account for how learners actually experience personalisation features, how instructors operationalise them in practice, or how contextual factors (e.g. discipline, cohort sise, digital literacy) mediate their effectiveness. This limitation reflects the study's intentional focus on platform capability rather than implementation outcomes, but it nonetheless constrains claims about pedagogical impact.

These limitations point to several avenues for future research. Most critically, subsequent studies should incorporate pilot implementations or design-based research cycles that examine how selected Moodle tools are enacted in real learning environments and how learners perceive agency, adaptivity, and usefulness. Mixed-methods approaches combining learning analytics, survey data, and qualitative learner feedback would allow validation of the framework-based mappings presented in this study and enable examination of alignment between designed and experienced personalization.

Future research should also explore the evolving role of AI-driven and data-intensive plugins, particularly those integrating predictive analytics, recommendation engines, or generative feedback. Such investigations would extend the PLDF analysis beyond rule-based adaptivity toward more autonomous personalization models, while also critically examining ethical concerns related to data use, transparency, and learner control. In addition, comparative studies across LMS platforms or institutional contexts could further illuminate how system architecture, governance, and pedagogical culture shape the balance between automation, instructor control, and learner agency.

Taken together, these directions position the present study not as an endpoint but as a conceptual and methodological foundation for empirically grounded, theory-informed research on personalised learning within LMS environments. By clarifying Moodle's personalization affordances and constraints through the PLDF lens, this work establishes a basis for future inquiry into how personalised e-learning can be designed, implemented, and experienced more effectively in higher education.

Conclusion and Recommendations

This study sets out to examine Moodle's potential to support personalised e-learning through a systematic application of the Personalised Learning Design Framework (PLDF). By mapping selected Moodle tools and plugins against the framework's five components, the analysis provides a structured account of how personalization is currently operationalised within a widely adopted learning management system. The findings demonstrate that Moodle offers substantial capacity for adaptive content delivery, differentiated assessment, and data-informed instructional adjustment, particularly through instructor-configured rules and performance-driven mechanisms.

However, the framework-based analysis also reveals a clear imbalance in how PLDF components are realised. While Moodle aligns strongly with instructional elements and data use, personalization remains predominantly instructor-centreed and design-time driven, with limited support for learner-initiated customization or dynamically evolving learning pathways. Learner agency, where present, is most often enacted as guided interaction rather than substantive control over learning trajectories. From a PLDF perspective, this positions Moodle less as an autonomous adaptive system and more as a personalization-enabling infrastructure whose pedagogical impact depends heavily on intentional instructional design.

These findings carry several practical implications for institutions and instructional designers. Rather than relying on isolated tools, educators should adopt strategic combinations of Moodle features such as Conditional Activities, H5P, and analytics-enabled assessments to balance instructional control with meaningful learner engagement. Professional development initiatives should therefore prioritise not only technical training, but also pedagogical design competence, particularly in leveraging data to inform adaptive decisions while preserving learner agency. At the platform level, continued plugin development that foregrounds learner choice and ethical, transparent automation would further strengthen Moodle's alignment with contemporary personalization principles.

Beyond its practical implications, this study contributes methodologically by demonstrating the value of PLDF as an evaluative lens for learning management systems. The rubric-guided mapping approach illustrates how framework-based analysis can surface underlying design orientations, trade-offs, and structural constraints that may not be evident through feature-level descriptions alone. In doing so, the study advances understanding of how personalised learning is designed for within LMS environments, as distinct from how it may ultimately be experienced in practice.

In conclusion, Moodle possesses considerable potential to support personalised e-learning, but the realization of this potential is contingent upon deliberate design choices rather than default system behaviour. By clarifying where Moodle aligns with and falls short of the PLDF components, this study provides both conceptual insight and practical guidance for educators seeking to create more inclusive, responsive, and learner-centreed digital learning environments.

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