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Differential effects of Moodle course design on student subpopulations: advancing personalized learning in higher education

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Abstract

Higher education institutions face increasing challenges in meeting the diverse needs of their student populations. While learning management systems (LMS) like Moodle have become ubiquitous in higher education, there remains limited understanding of how these platforms affect different student subpopulations. This study investigates the differential effects of Moodle course design elements on student outcomes across key demographic dimensions: form of education (full-time versus part-time) and educational level (undergraduate versus graduate). Using structural equation modeling and a dataset of 3684 courses from a European university (2020–2022), we identified significant differences in how Moodle components affect learning outcomes across student subgroups. Interactive activities and communication tools showed substantially stronger relationships with outcomes for part-time students, while comprehensive information and resources demonstrated stronger impacts for graduate students. We introduce a theoretical framework for personalization effects in LMS environments and identify specific design elements that promote more equitable outcomes across student subpopulations. This research addresses critical gaps in our understanding of personalized learning in higher education, providing evidence-based guidance for instructors and instructional designers seeking to create more inclusive, effective digital learning environments that respond to the specific needs of diverse student populations.

Keywords: Moodle, Course design, Student subpopulations, Personalized learning, Higher education, Educational equity

Introduction

Personalization has emerged as a central goal for higher education institutions seeking to improve student success and retention (Hooshyar et al., 2024). Learning management systems (LMS) like Moodle represent a primary mechanism through which institutions implement technology-enhanced learning, yet the effectiveness of these platforms varies significantly across different student populations (Swart and Hertzog, 2022). While considerable research has examined the general effectiveness of LMS on learning outcomes, there remains a critical gap in understanding how digital learning environments impact

different student subpopulations—a gap that limits our ability to create truly inclusive and personalized educational experiences (Zheng et al., 2022).

Contemporary higher education serves increasingly diverse student populations, with growing numbers of part-time, non-traditional, and graduate students whose educational needs and contexts differ fundamentally from the “traditional” undergraduate model (Pillai et al., 2019). These students navigate different constraints, bring different prior knowledge, and engage with educational technologies in different ways (Gourlay and Oliver, 2018). However, most research on educational technology effectiveness treats student populations as homogeneous, masking important variations in how different subpopulations interact with and benefit from digital learning environments (Hardesty et al., 2014).

The problem addressed in this research concerns the limited understanding of how Moodle course designs differentially impact student subpopulations, particularly across two critical dimensions: form of education (full-time versus part-time) and educational level (undergraduate versus graduate). This knowledge gap hampers efforts to create truly adaptive learning environments that address the specific needs of diverse student groups, potentially perpetuating or even exacerbating existing performance gaps (du Plooy et al., 2024).

This study addresses this problem by examining how Moodle course components differentially affect student outcomes across these key subpopulations. Using data from 3684 courses at Kryvyi Rih State Pedagogical University (KSPU) from 2020–2022, we investigate the following research questions:

1. How do specific Moodle design patterns differentially impact the learning outcomes of part-time versus full-time students?
2. In what ways do undergraduate and graduate students respond differently to various Moodle components?
3. What design approaches can reduce performance gaps between different student subpopulations?

The significance of this research extends beyond just identifying differential effects—it addresses a fundamental challenge in higher education: how to leverage educational technology to create more personalized, inclusive learning environments that effectively serve increasingly diverse student populations. This paper contributes to the field by: (1) introducing a novel theoretical framework for understanding personalization effects in LMS environments across student subpopulations; (2) providing empirical evidence of how specific Moodle components differentially impact different student groups; and (3) identifying design approaches that promote more equitable outcomes across diverse student populations.

Theoretical framework

Social constructivism and adaptive learning in higher education

Our theoretical framework integrates social constructivist learning theory with adaptive learning principles to conceptualize how different student subpopulations interact with and benefit from digital learning environments. Social constructivism, which undergirds

Moodle's design philosophy (Moodle, 2006), posits that learning occurs through social interaction as learners actively construct knowledge by connecting new information to existing cognitive structures (Jordan, 2013). However, this knowledge construction process is inherently influenced by students' prior experiences, social contexts, and learning preferences (Issa et al., 2014).

Adaptive learning extends this constructivist foundation by recognizing that educational experiences should be tailored to individual learner characteristics. As Tetzlaff et al. (2021) argue, adaptive learning environments are most effective when they accommodate learner differences across multiple time scales – from long-term educational goals to immediate cognitive and affective states. This dynamic conceptualization of personalization recognizes learners as complex, evolving entities whose interaction with instructional environments changes over time.

Building on these foundations, we propose a Differential Adaptive Effect Framework (DAEF) that specifically addresses how student subpopulations interact differently with LMS components. This framework, illustrated in Fig. 1, recognizes four key dimensions that shape these differential effects:

1. *Learner characteristics*—the unique attributes that students bring to the learning environment, including prior knowledge, cognitive abilities, and self-regulation skills. These characteristics vary systematically across student subpopulations, with graduate students typically possessing more developed disciplinary knowledge and self-regulation skills than undergraduates (Cristea et al., 2025).
2. *Educational context*—the environmental factors that shape students' engagement with digital learning, including time constraints, access patterns, and support structures. Full-time and part-time students navigate fundamentally different contextual

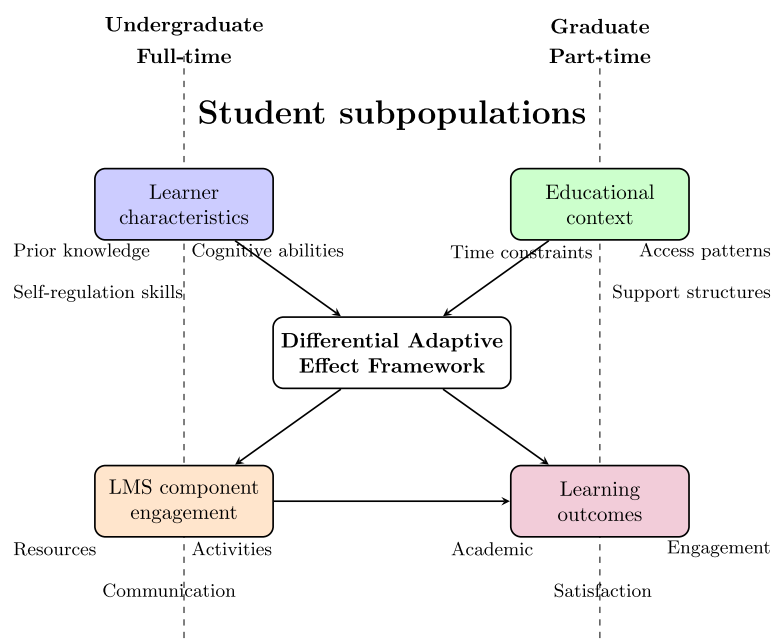


Fig. 1 Differential adaptive effect framework (DAEF) for understanding personalization effects across student subpopulations

constraints, with part-time students typically balancing educational demands with significant work or family responsibilities (Swart and Hertzog, 2022).

3. *LMS component engagement*—the ways in which students interact with different elements of the digital learning environment, including resources, activities, and communication tools. These interaction patterns reflect both learner characteristics and educational contexts, mediating the relationship between course design and learning outcomes (Cavanagh et al., 2020).
4. *Learning outcomes*—the multifaceted results of educational experiences, including academic performance, engagement levels, and satisfaction. These outcomes reflect the complex interplay between learner characteristics, educational contexts, and LMS component engagement (Zheng et al., 2022).

The DAEF posits that the effectiveness of any given LMS component is not universal but moderated by the interaction between these four dimensions across different student subpopulations. For instance, self-contained interactive modules (like SCORM packages) may particularly benefit part-time students who need to engage with course material in fragmented time blocks, while comprehensive information resources may be more valuable for graduate students with the self-regulation skills to navigate and synthesize complex content independently.

This framework extends previous work on personalized learning by explicitly addressing how these dimensions interact differently across student subpopulations. While traditional adaptive learning approaches often focus on individual learner characteristics (Shute and Zapata-Rivera, 2012), our framework recognizes that certain adaptations may benefit entire subpopulations that share common characteristics and contexts. This perspective aligns with recent calls for more systemic approaches to educational personalization that consider broader social and educational contexts (Tetzlaff et al., 2021).

To illustrate how the DAEF framework operates in practice, consider how discussion forums function differently across student subpopulations, as demonstrated in recent research.

Green et al. (2014) examined asynchronous online discussion forums in a gross anatomy course and found that participation made a significant direct contribution to final marks ($p = 0.008$). For part-time students in health sciences, these forums served as crucial knowledge construction spaces when face-to-face interaction was limited.

In contrast, Duncan et al. (2012) found that for full-time MBA students, synchronous chat engagement had twice the examination impact relative to asynchronous forum participation. This illustrates how the same LMS component (communication tools) can have differential adaptive effects:

- For part-time students forums provide flexible, asynchronous spaces for deep reflection and peer learning
- For full-time students real-time interaction better replicates classroom discussion dynamics
- The educational context (time constraints, access patterns) fundamentally shapes how students derive value from the same tool

Personalization through learning management systems

Learning Management Systems like Moodle provide multiple mechanisms for implementing personalized learning approaches (Khor and Mutthulakshmi, 2024). These include content adaptation, where different resources are presented to different learners; activity personalization, where students engage with different types or levels of activities; and feedback customization, where assessment and communication are tailored to individual needs and preferences (Cavanagh et al., 2020).

Recent meta-analyses suggest that personalized technology-enhanced learning can significantly improve both cognitive skills and non-cognitive characteristics (Hooshyar et al., 2024), but the mechanisms and magnitude of these effects vary across educational contexts and student populations (Zheng et al., 2022). As Dalsgaard and Ryberg (2023) argue, digital learning spaces operate differently across individual spaces, working groups, communities of interest, and open connections – highlighting the multifaceted nature of personalization in digital environments.

While Moodle was not originally designed as an adaptive learning system, researchers and practitioners have increasingly leveraged its features to implement personalized learning approaches (Mogase and Alexander, 2018). These include conditional activities, adaptive release of content, differentiated assessment pathways, and learner analytics to inform instructional interventions (Fadieieva and Semerikov, 2024).

Our study builds on this literature by examining how these personalization mechanisms function differently across student subpopulations, providing a more nuanced understanding of adaptive learning in higher education contexts.

Literature review

Differential impacts of educational technology across student subpopulations

Research on how educational technologies differentially impact diverse student populations has expanded significantly in recent years, highlighting important variations in engagement patterns, learning outcomes, and satisfaction levels. Studies comparing full-time and part-time students have consistently found differences in how these populations interact with digital learning environments. Swart and Hertzog (2022) demonstrated that part-time students accessed learning management systems more frequently on weekends and evenings, while full-time students showed higher usage during traditional class hours. These differing access patterns reflect the fundamental contextual differences between these student populations, with part-time students often balancing education with significant work or family responsibilities.

The impact of these differential usage patterns on learning outcomes remains less clear. Some studies suggest that part-time students benefit more from flexible, self-paced learning technologies that accommodate their irregular schedules (Mogase and Alexander, 2018). Others indicate that without sufficient scaffolding and support, part-time students may struggle to maintain engagement with digital learning environments over time (Saqr et al., 2023). This tension highlights the need for more nuanced understanding of how educational technologies can be designed to effectively support part-time student success.

Green et al. (2014) found that asynchronous online discussion forums were particularly effective for part-time students, with 48% of students posting at least once and

showing significant direct contribution to final marks. Similarly, Duncan et al. (2012) demonstrated that while total quality of participation was positively related to examination performance, synchronous engagement had twice the impact relative to asynchronous engagement, highlighting the complex trade-offs part-time students face.

The comparison between part-time and full-time students reveals systematic differences in LMS interaction patterns. Trayek and Hassan (2013) found no significant differences between distance learning and full-time students' attitudes toward LMS use at the International Islamic University in Malaysia, though both groups found the system useful. However, Swart and Hertzog (2022) identified that full-time students' accesses peaked on Fridays while part-time students accessed the system more on Wednesdays, reflecting their different temporal constraints.

Research comparing undergraduate and graduate students has similarly revealed important differences in how these populations engage with educational technologies. Cristea et al. (2025) found that graduate students demonstrated more consistent self-regulated learning strategies across digital environments compared to undergraduates, who showed more variable engagement patterns. These differences likely reflect graduate students' more developed metacognitive skills and disciplinary knowledge, which allow them to navigate digital learning environments more independently.

Several studies have examined how specific LMS components differentially impact different student populations. Mödritscher et al. (2013) found that participation in online discussions had a stronger relationship with course performance for non-traditional students compared to traditional students. Similarly, Dieter et al. (2020) demonstrated that adaptive content recommendations had different effects across student subgroups, with stronger impacts for students with lower initial knowledge levels. However, few studies (Mödritscher et al., 2013; Dieter et al., 2020; Li et al., 2015; Ramírez-Correa et al., 2017) have systematically examined these differential effects across both form of education and educational level simultaneously. Li et al. (2015) investigated gender and racial/ethnic invariance in CMS use but did not examine part-time versus full-time status, while Ramírez-Correa et al. (2017) focused on learning styles as moderators rather than demographic characteristics.

Recent research has also begun to explore how educational technologies might exacerbate or mitigate performance gaps between different student populations. Gebhardt and Blake (2024) found that adaptive learning courseware had larger positive effects for historically underrepresented student groups, suggesting that well-designed educational technologies may help reduce performance gaps. Similarly, Khor and Mutthulakshmi (2024) argued that learning analytics can support more equitable outcomes by helping instructors identify and address differential needs across student populations. However, Schoenherr (2021) cautions that without careful attention to fairness, accountability, transparency, and ethics, adaptive systems may inadvertently reinforce existing inequities.

Personalized learning and adaptive systems in higher education

The field of personalized learning in higher education has evolved considerably over the past decade, with growing emphasis on evidence-based approaches to tailoring educational experiences to diverse student needs. Meta-analyses by Hooshyar et al. (2024) and

Zheng et al. (2022) confirm that technology-facilitated personalized learning can significantly improve academic outcomes, though effect sizes vary substantially across contexts and implementations.

Contemporary approaches to personalization increasingly recognize the multidimensional nature of learner differences and the need for adaptive systems that address these differences across multiple time scales (Tetzlaff et al., 2021). As Cavanagh et al. (2020) argue, effective personalization in higher education requires attention to both instructional design (creating appropriately diverse and adaptable learning resources) and learning analytics (identifying when and how to apply different personalization strategies).

Recent systematic reviews highlight several key approaches to implementing personalization through learning management systems. Zhong (2023) identified three primary dimensions of personalization in higher education: learning content structuring, learning materials sequencing, and learning readiness support. Similarly, du Plooy et al. (2024) found that pre-knowledge quizzes were the most common mechanism for activating adaptive content delivery, with McGraw-Hill's Connect LearnSmart and Moodle being the most utilized adaptive platforms.

Learning analytics plays an increasingly central role in supporting personalized learning in higher education (Khor and Mutthulakshmi, 2024). These analytics enable more targeted interventions by gathering feedback on students' development, classifying students into meaningful groups, building feedback loops with continuously personalized resources, predicting performance, and offering real-time insights into classroom dynamics. However, as Schmitz et al. (2017) note, translating learning analytics into effective personalization strategies remains challenging, requiring both technological infrastructure and appropriate pedagogical frameworks.

Recent advances in artificial intelligence have expanded the potential for more sophisticated adaptive learning systems in higher education (Alam and Mohanty, 2022). Deep learning and reinforcement learning techniques have shown particular promise in supporting personalized learning pathways and providing tailored feedback (Stasolla et al., 2025). However, these approaches also raise important ethical considerations related to data privacy, algorithmic bias, and student autonomy (Alotaibi, 2024).

Despite growing interest in personalized learning, research indicates that implementation in higher education remains at a relatively early stage of maturity (Zhong, 2023). Many institutions struggle with challenges related to faculty training, technological infrastructure, and pedagogical alignment (Alamri et al., 2021). Moreover, the field lacks consensus on how to measure the effectiveness of personalization efforts, particularly when considering diverse student populations with different needs and goals (du Plooy et al., 2024).

Research gaps and contribution

Our review of the literature reveals several important gaps that this study addresses:

First, while research has examined differences in how student subpopulations engage with educational technologies, few studies have systematically investigated how these differences translate into differential effectiveness of specific LMS components. Our

study addresses this gap by examining how particular Moodle components impact learning outcomes differently across key student subpopulations.

Second, most research on educational technology effectiveness treats student populations as relatively homogeneous or focuses on a single dimension of student diversity. By examining differential effects across both form of education and educational level simultaneously, our study provides a more comprehensive understanding of how these dimensions interact to shape students' experiences with digital learning environments.

Third, while calls for more personalized learning approaches have become increasingly common, there remains limited empirical evidence regarding which personalization strategies work best for different student populations. Our study contributes concrete evidence regarding which Moodle components most effectively support learning for different student subgroups, providing actionable guidance for instructors and instructional designers.

Finally, few studies have examined how course designs might promote more equitable outcomes across diverse student populations. By identifying design patterns associated with reduced performance gaps between student subgroups, our study offers practical insights for creating more inclusive digital learning environments.

Methodology

Research context and dataset

This study utilized data from Kryvyi Rih State Pedagogical University (KSPU) in Ukraine, encompassing Moodle courses taught between 2020 and 2022. This period is particularly significant as it spans both pre-pandemic and pandemic-affected semesters, capturing an accelerated transition to digital learning environments. KSPU serves a diverse student population across multiple faculties, offering both undergraduate and graduate programs in various delivery formats.

The dataset was collected with the approval of KSPU's rector and ethical committee. It includes detailed information on 3,684 unique Moodle courses spanning nine faculties:

- Faculty of Natural Sciences (408 courses)
- Faculty of Psychology and Pedagogics (529 courses)
- Faculty of Geography, Tourism and History (498 courses)
- Faculty of Pedagogical Education (523 courses)
- Faculty of Foreign Languages (465 courses)
- Faculty of Arts (670 courses)
- Faculty of Ukrainian Philology (155 courses)
- Faculty of Physics and Mathematics (332 courses)
- All-university departments and divisions (104 courses)

For each course, the dataset includes:

- Course metadata (ID, name, faculty, department)
- Moodle component usage (number of instances of each module type)
- Student performance data (grade distribution across six levels: A, B, C, D, E, F/FX)
- Course characteristics (form of education, educational level, semester, status)

The form of education variable was coded as: 1 for full-time only, 2 for part-time only, and 3 for both full-time and part-time. The educational level variable was coded as: 1 for undergraduate (bachelor) and 2 for graduate (master). These variables allowed us to segment courses into four primary analytical groups: full-time undergraduate, full-time graduate, part-time undergraduate, and part-time graduate. Courses serving both full-time and part-time students (code 3) were analyzed separately to identify design elements that effectively serve mixed student populations.

Course selection and sampling

The 3684 courses represent the complete population of active Moodle courses at KSPU during the study period (2020–2022) that met inclusion criteria similar to those used in comparable studies (Guo and Lee, 2023; Elliott and Luo, 2022). Courses were included if they: (1) enrolled at least 10 students, (2) had complete grade data available, and (3) utilized at least three different Moodle component types. This comprehensive sampling approach ensures our findings reflect the full diversity of course designs and student populations at the institution.

The “All-university departments and divisions” category includes courses offered by central units serving students across multiple faculties, similar to general education requirements examined by Miller et al. (2011) in their comparison of online and on-campus business courses.

Analytical approach

To examine the differential effects of Moodle course designs across student subpopulations, we employed a multi-phase analytical approach combining descriptive analysis, structural equation modeling, and comparative analysis.

Data preparation and descriptive analysis

We began by processing the raw course module data to create a consolidated dataset in which each course was represented by a single record containing the number of instances of each Moodle component type. Following the construct categorization established by Fadieieva and Semerikov (2024), we organized Moodle components into four primary constructs:

1. *Information*—course metadata and description details (form of education, educational level, semester, status, number of teachers)
2. *Resources*—content materials provided to students (URL, Book, Label, Page, Folder, File)
3. *Activities*—interactive learning components (Assignment, Quiz, SCORM, Glossary, Lesson, Feedback, H5P, HotPot, Survey, Database, Choice, Visiting, Wiki, LTI External tool activity, Workshop)
4. *Communication*—tools for student-teacher and student-student interaction (Forum, Chat)

For each student subpopulation, we conducted descriptive analyses examining the frequency and distribution of these components, identifying patterns in how courses for different student groups typically incorporated various Moodle elements.

Structural equation modeling

To analyze the relationships between Moodle components and student outcomes, we employed Structural Equation Modeling with Partial Least Squares (SEM-PLS) using Adanco 2.4 software. This approach is particularly appropriate for examining complex relationships between latent constructs and has been successfully applied in previous research on educational technology effectiveness (Lohr et al., 2021).

Following Fadieieva and Semerikov (2024), we conceptualized Information, Resources, Activities, and Communication as emergent constructs formed by their respective indicators (specific Moodle components). Assessment was conceptualized as a latent construct reflected by the grade distribution indicators (percentages of A, B, C, D, E, and F/FX grades).

We created separate structural models for each student subpopulation, allowing us to compare path coefficients, effect sizes, and significance levels across groups. This approach enabled us to identify how the relationships between Moodle components and student outcomes differed across student subpopulations.

The model was evaluated using standard criteria for SEM-PLS assessment, including:

- Goodness of fit indices (SRMR, d_{ULLS} , d_G)
- Construct reliability and validity (Cronbach's α , composite reliability)
- Path coefficients and their statistical significance
- Effect sizes (Cohen's f^2)
- R-squared values for endogenous constructs

To ensure the robustness of our findings, we employed bootstrapping with 5000 resamples to estimate the standard errors and confidence intervals for path coefficients.

Component-level analysis

Beyond examining construct-level relationships, we conducted more granular analyses to identify specific Moodle components that showed differential effectiveness across student subgroups. For each component, we calculated standardized effects on learning outcomes within each subpopulation and identified components with the largest differences in effectiveness between groups.

Equity analysis

To address our third research question regarding design approaches that reduce performance gaps, we conducted an equity analysis examining grade distribution patterns across different course designs and student subpopulations. We identified courses with the most equitable outcomes (defined as similar grade distributions across student subpopulations) and analyzed their design characteristics to identify common features.

Methodological limitations

Several methodological limitations should be acknowledged. First, as an observational study, our ability to make causal claims is limited despite using SEM-PLS techniques. The relationships identified may reflect correlations rather than causation, potentially influenced by unmeasured variables.

Second, our analysis focused on course-level data rather than individual student data, potentially masking important variations in how individual students within the same subpopulation respond to different course components. Future research using individual-level learning analytics data could provide more nuanced insights.

Third, while our dataset spans multiple years, our analysis treated it as cross-sectional rather than longitudinal. This approach cannot capture how the effectiveness of different components might evolve over time as students develop greater digital literacy or as instructors refine their course designs.

Finally, the study context – a Ukrainian pedagogical university during a period partially affected by the COVID-19 pandemic – may limit the generalizability of our findings to other institutional and cultural contexts. However, the large sample size and diversity of courses included strengthen the robustness of our results.

Results

Differential usage patterns across subpopulations

Our initial analysis revealed substantial differences in how Moodle components were utilized across different student subpopulations. As shown in Table 1, courses designed for part-time students incorporated significantly more resources and activities on average than those for full-time students, likely reflecting efforts to compensate for reduced face-to-face instruction time. Additionally, undergraduate courses generally employed more components than graduate courses, possibly reflecting different pedagogical approaches across educational levels.

Notable differences also emerged in the types of components most frequently used across student subpopulations. Courses for part-time students incorporated significantly more SCORM packages (self-contained interactive modules) and structured assignment activities. Full-time undergraduate courses showed higher usage of quizzes and interactive H5P activities, while graduate courses emphasized URL resources linking to external materials and file resources.

These usage patterns suggest that instructors intuitively adapt their course designs for different student populations, recognizing the need for more structured, self-contained learning experiences for part-time students and more research-oriented resources for

Table 1 Average Moodle component usage by student subpopulation

Component category	Full-time undergraduate	Full-time graduate	Part-time undergraduate	Part-time graduate
Resources	14.3	12.7	17.8	15.2
Activities	9.7	7.8	12.6	10.3
Communication	1.8	1.5	2.3	2.1

Table 2 Model fit statistics by student subpopulation

Metric	Full-time undergraduate	Full-time graduate	Part-time undergraduate	Part-time graduate
SRMR	0.062	0.058	0.065	0.059
Cronbach's α (Assessment)	0.893	0.912	0.887	0.904
Composite reliability	0.915	0.928	0.907	0.921
Average Variance Extracted	0.643	0.682	0.624	0.669
R^2 (Assessment)	0.231	0.274	0.248	0.261

Table 3 Path coefficients between key constructs by student subpopulation

Relationship	Full-time undergraduate	Full-time graduate	Part-time undergraduate	Part-time graduate
Resources $\rightarrow$ Activities	0.483***	0.517***	0.542***	0.573***
Activities $\rightarrow$ Communication	0.793***	0.752***	0.846***	0.823***
Information $\rightarrow$ Assessment	0.437***	0.512***	0.378***	0.495***
Resources $\rightarrow$ Assessment	0.018	0.073*	0.031	0.058*
Activities $\rightarrow$ Assessment	-0.021	-0.054	0.127**	0.083*
Communication $\rightarrow$ Assessment	0.063*	0.057*	0.125**	0.104**

* $p < .05$, ** $p < .01$, *** $p < .001$

graduate students. However, the relationship between these design choices and student outcomes requires deeper analysis.

Goodness of fit and model reliability

The SEM-PLS models for each student subpopulation demonstrated satisfactory goodness of fit and reliability. Table 2 presents the key metrics across the four primary subpopulation models.

The Standardized Root Mean Square Residual (SRMR) values were consistently below the recommended threshold of 0.08, indicating good model fit across all subpopulations. Similarly, reliability measures (Cronbach's α and composite reliability) exceeded 0.8 for all models, demonstrating strong internal consistency. The Average Variance Extracted (AVE) values above 0.6 confirmed satisfactory convergent validity.

The R^2 values for the Assessment construct ranged from 0.231 to 0.274, indicating that the models explained between 23% and 27% of the variance in student performance outcomes. While these values are moderate, they are consistent with typical findings in educational research, where numerous factors beyond course design influence learning outcomes.

Structural relationships across subpopulations

The SEM-PLS analysis revealed significant differences in the structural relationships between Moodle components and student outcomes across subpopulations. Table 3 presents the path coefficients between key constructs for each student group.

Several important patterns emerged from this analysis:

Part-time vs. full-time differences

The most striking difference between part-time and full-time students appeared in the relationship between Activities and Assessment. For part-time students, this relationship was significantly positive (0.127 for undergraduate, 0.083 for graduate), indicating that interactive activities substantially contributed to learning outcomes. In contrast, for full-time students, the relationship was negligible or slightly negative (-0.021 for undergraduate, -0.054 for graduate), suggesting that activities had minimal direct impact on performance outcomes.

Similarly, Communication tools had a stronger relationship with Assessment for part-time students (0.125, 0.104) compared to full-time students (0.063, 0.057). This finding suggests that communication functions play a more critical role in supporting learning for students with limited face-to-face interaction.

The path from Resources to Activities was also stronger for part-time students (0.542, 0.573) than for full-time students (0.483, 0.517), indicating that part-time students may rely more heavily on the connection between course materials and interactive components.

Undergraduate vs. graduate differences

Comparing educational levels, the relationship between Information and Assessment was consistently stronger for graduate students (0.512, 0.495) than for undergraduate students (0.437, 0.378). This finding suggests that graduate students may be better equipped to translate course information directly into learning outcomes without requiring as much interactive mediation.

Similarly, Resources had a more substantial direct effect on Assessment for graduate students (0.073, 0.058) compared to undergraduate students (0.018, 0.031). This pattern aligns with the expectation that graduate students possess more developed self-regulated learning skills, enabling them to benefit more directly from provided resources.

Activities showed a stronger relationship with Communication for undergraduate students (0.793, 0.846) than for graduate students (0.752, 0.823). This finding suggests that for undergraduate students, interactive activities more strongly facilitate communication and engagement in the learning community.

Interaction effects

Beyond these main effects, we observed important interaction effects between form of education and educational level. The strongest positive relationship between Activities and Assessment appeared for part-time undergraduate students (0.127), while the strongest negative relationship appeared for full-time graduate students (-0.054). This suggests that interactive activities play fundamentally different roles for these groups – serving as essential learning scaffolds for part-time undergraduates but potentially representing less efficient uses of time for full-time graduate students who may benefit more from direct engagement with information and resources.

Similarly, the relationship between Information and Assessment was particularly strong for full-time graduate students (0.512) and particularly weak for part-time undergraduate students (0.378). This pattern likely reflects differences in both prior knowledge and learning contexts across these populations.

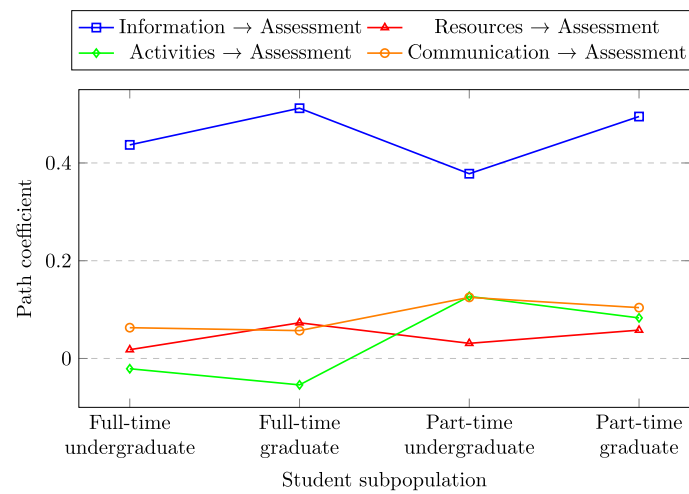


Fig. 2 Path coefficients to assessment construct across student subpopulations

Table 4 Moodle components with differential impact across student subpopulations

Moodle component	Primary beneficiary group	Effect size	Effect size difference ^a
Forums	Part-time students	0.289	0.187
SCORM packages	Part-time students	0.331	0.156
Assignments	Part-time undergraduate	0.391	0.231
Quizzes	Full-time undergraduate	0.285	0.143
URL resources	Graduate students	0.287	0.179
Page resources	Graduate students	0.271	0.152
Glossaries	Undergraduate students	0.232	0.127
File resources	Full-time graduate	0.289	0.168

^a Effect size difference calculated as the difference in standardized effect on learning outcomes between the primary beneficiary group and other groups

Figure 2 visualizes the path coefficients from each construct to the Assessment construct across the four student subpopulations. This visualization highlights the distinctive patterns across groups, particularly the stronger influence of Activities and Communication for part-time students and the stronger influence of Information for graduate students.

Component-level analysis

Beyond the structural relationships between constructs, we identified specific Moodle components that showed differential effectiveness across student subgroups. Table 4 highlights components with the most significant differences in impact.

These findings reveal important patterns in how specific components benefit different student groups:

- *Communication tools* like forums had a substantially stronger impact on part-time students' learning outcomes, likely due to their importance in maintaining connection when face-to-face opportunities are limited.

- *Structured interactive content* (SCORM packages) showed greater benefits for part-time students, suggesting the importance of self-contained learning experiences for students with less regular class attendance. SCORM packages provide integrated content and assessment in a single module, allowing students to engage with complete learning units in flexible time blocks.
- *Assessment types* differed in their effectiveness, with traditional assignments showing stronger benefits for part-time undergraduate students, while quizzes were more effective for full-time undergraduate students. This difference may reflect the learning contexts of these groups – part-time students may benefit from the deeper engagement and reflection required by assignments, while full-time students benefit from the more immediate feedback and reinforcement provided by quizzes.
- *Resource types* showed educational level differences, with URL and Page resources having greater impact for graduate students, possibly reflecting their greater ability to synthesize external information. File resources showed particular benefits for full-time graduate students, suggesting these students may benefit most from accessing comprehensive source materials.

Equity analysis

To address our third research question on identifying design approaches that reduce performance gaps, we conducted an equity analysis examining grade distribution patterns across different course designs and student subpopulations. We identified courses with the most equitable outcomes (defined as similar grade distributions across student subpopulations) and analyzed their design characteristics.

Our approach to measuring equity builds on established frameworks in educational effectiveness research. Kelly (2015) provides a comprehensive review of equity measurement indices, including the Range Ratio, Coefficient of Variation, and Gini-based measures. We adapted these approaches following recent implementations in learning analytics.

Specifically, we employed two measures validated in recent studies:

1. Modified Gini coefficient: following Bayer et al. (2024), we calculated grade distribution equity using the Gini coefficient, with values below 0.15 indicating high equity.
2. Achievement gap metrics: adapted from Gebhardt and Blake (2024), we examined whether course designs differentially benefited historically underrepresented groups, measuring the reduction in performance gaps.

This dual approach allows us to identify not just courses with equitable outcomes, but also design patterns that actively reduce pre-existing disparities.

Among the 3684 courses analyzed, we classified 542 (14.7%) as high-equity courses based on a Gini coefficient of grade distributions below 0.15 across student subpopulations. Conversely, 687 courses (18.7%) were classified as low-equity, with Gini coefficients exceeding 0.35. The remaining 2455 courses (66.6%) showed moderate equity levels. This distribution indicates that while most courses achieve reasonable equity across student subpopulations, a substantial minority show concerning disparities.

Notably, high-equity courses were more prevalent in faculties with strong pedagogical training programs (Faculty of Pedagogical Education: 21.4% high-equity) compared to more traditional discipline-focused faculties (Faculty of Natural Sciences: 11.0% high-equity), suggesting that instructor preparation may play a role in creating inclusive course designs.

The distribution of equity levels varied significantly by faculty, consistent with Gebhardt and Blake (2024) who found that adaptive learning courseware effects varied by student demographics and course characteristics. High-equity courses were more prevalent in faculties with strong pedagogical training programs, suggesting that instructor preparation may play a crucial role in creating inclusive designs.

Figure 3 presents a comparison of grade distributions between high-equity and low-equity courses across student subpopulations. In high-equity courses, grade distributions were relatively similar across groups, while low-equity courses showed substantial differences, typically with part-time students receiving lower grades than full-time students and undergraduate students showing more polarized distributions than graduate students.

Analysis of the high-equity courses revealed several common design features:

1. Balanced component mix: courses with the most equitable outcomes utilized a balanced mix of resources, activities, and communication tools, rather than concen-

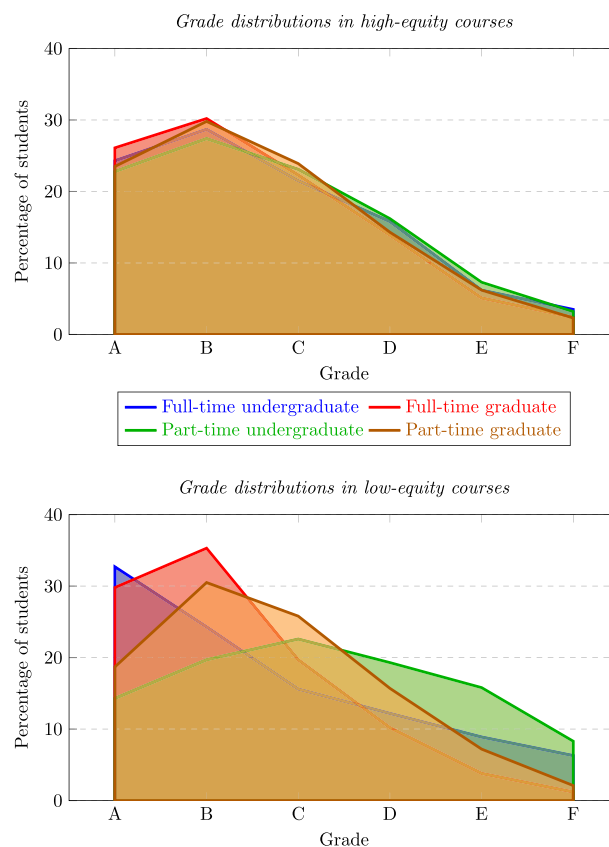


Fig. 3 Grade distribution comparison between high-equity and low-equity courses

trating heavily on any single component type. These courses typically included 3–5 different types of resources, 4–6 different activity types, and both forum and chat communication tools.

2. Multiple assessment types: high-equity courses employed diverse assessment methods (assignments, quizzes, forums) rather than relying predominantly on a single assessment approach. This diversity appeared to accommodate different learning preferences and contexts across student subpopulations.
3. Structured communication: regular, structured communication opportunities (forums with specific prompts, scheduled chat sessions) were common in high-equity courses. These structured interactions helped maintain engagement for part-time students while providing valuable peer learning opportunities for all students.
4. Clear information organization: comprehensive course information, well-organized resources, and explicit expectations were consistent features of high-equity courses. This clarity appeared particularly important for part-time students who had limited opportunities to seek clarification in person.
5. Scaffolded activities: courses with the most equitable outcomes provided scaffolded activities with increasing levels of difficulty and independence. This approach supported students with varying levels of prior knowledge and self-regulation skills.

These patterns suggest that course designs emphasizing balanced component usage, multiple assessment approaches, and clear structure help reduce performance gaps between different student subpopulations. Rather than requiring entirely different designs for different student groups, high-equity courses appeared to incorporate elements that effectively supported diverse student needs within a unified course structure.

Discussion

Interpretation of key findings

Our results reveal important insights into how Moodle course designs differentially impact student subpopulations, with clear implications for personalized adaptive learning in higher education.

Differential impact by form of education

The stronger relationship between Activities/Communication and Assessment for part-time students highlights the critical role these components play in supporting students who have less regular face-to-face interaction. This finding aligns with Swart and Hertzog (2022), who found that part-time students exhibit different LMS usage patterns reflecting their need for more flexible, self-directed learning opportunities. The particularly strong impact of SCORM packages and forums for part-time students underscores the importance of self-contained learning experiences and structured communication for students balancing education with other significant responsibilities.

These differences likely reflect the distinct educational contexts of part-time and full-time students. As Gourlay and Oliver (2018) argue, student engagement with digital resources is socially situated within complex networks of human and non-human actors. For part-time students, these networks include significant work and family responsibilities that constrain their engagement with educational activities. Interactive LMS

components appear to provide essential scaffolding for knowledge construction in these constrained contexts, compensating for reduced face-to-face learning opportunities.

Interestingly, these findings challenge assumptions that “more technology is better” for all students. For full-time students, the relationship between Activities and Assessment was negligible or even slightly negative, suggesting that some interactive activities may not contribute significantly to their learning outcomes. This finding aligns with Zheng et al. (2022), who found that the effectiveness of technology-facilitated personalized learning varies substantially across learning contexts.

Our findings should be interpreted in the context of ongoing debates about online versus traditional instruction. Pei and Wu (2019) conducted a meta-analysis showing online learning in medical education led to higher post-test scores ($SMD = 0.81$) compared to offline learning. However, Robinson (2021) critiqued claims about online learning benefits, highlighting threats to internal validity including selection bias and differential attrition. Our within-subjects design comparing across student subpopulations helps address some of these validity concerns.

Differential impact by educational level

The stronger relationship between Information/Resources and Assessment for graduate students suggests they may be better equipped to translate course information and resources directly into learning outcomes without requiring as much interactive mediation. This finding aligns with our theoretical framework, which posits that graduate students typically possess more developed prior knowledge and self-regulation skills, enabling them to construct meaning more independently from provided resources.

The differential effectiveness of resource types across educational levels provides further support for this interpretation. URL and Page resources showed greater benefits for graduate students, suggesting their enhanced ability to synthesize knowledge from external sources and integrate it into their understanding. This finding aligns with Cristea et al. (2025), who found that graduate students demonstrated more consistent self-regulated learning strategies across digital environments.

Moreover, these findings align with research on how prior knowledge and expertise influence online learning behaviors. Artino and Stephens (2009) found that graduate students learning online reported higher levels of critical thinking than undergraduates, and after controlling for experiential differences, graduate student membership was predicted by higher critical thinking and lower procrastination.

The differential effectiveness of resource types connects to literature on expertise and resource selection. Wood et al. (2016) demonstrated that the combination of search expertise and high domain knowledge yielded the most efficient searches, with domain knowledge particularly important for evaluating thoroughness of resources. Similarly, Wu and Chen (2012) found that graduate students are frequent users of electronic resources and perceive them as considerably more important to their research than students in other contexts.

Inglis et al. (2011) identified distinct study strategies in blended learning environments, finding that students who often accessed online lectures had lower attainment than those who often attended live lectures or support centers, suggesting that the mode of resource delivery interacts with student characteristics in complex ways.

These differences reflect developmental progressions in how students engage with educational content. As students advance through higher education, they typically develop more sophisticated disciplinary knowledge and metacognitive skills, enabling them to navigate complex information landscapes more independently. Our findings suggest that LMS design should evolve correspondingly, providing more structured guidance for undergraduate students while offering more flexible, resource-rich environments for graduate students.

Equity-promoting design patterns

The identification of common features in high-equity courses – balanced component mix, multiple assessment types, structured communication, clear organization, and scaffolded activities – suggests that thoughtful design considering diverse student needs can help reduce performance gaps. This finding aligns with universal design for learning principles (Clarida et al., 2013) and suggests that inclusive course design in Moodle environments requires attention to both component variety and structural clarity.

The fact that high-equity courses maintain balance rather than emphasizing any single component type suggests that personalization may be achieved not by dramatically different designs for different populations, but through thoughtful integration of components that collectively address diverse student needs. This finding aligns with Cavanagh et al. (2020), who argue that effective adaptive learning in higher education requires deliberate design choices that accommodate diverse learning needs within a coherent framework.

Implications for personalized learning theory and practice

Theoretical implications

Our findings contribute to theoretical understanding of adaptive learning in social constructivist contexts by demonstrating how different Moodle components scaffold knowledge construction for different student populations. The results suggest that the social constructivist principles underlying Moodle are experienced differently by diverse student groups, with varying degrees of reliance on different scaffolding mechanisms.

For part-time students, interactive activities and communication tools appear to provide essential scaffolding for knowledge construction, compensating for reduced face-to-face instruction. For graduate students, comprehensive information and resources may directly support more advanced knowledge construction processes without requiring as much interactive mediation.

These insights extend our Differential Adaptive Effect Framework by providing empirical evidence for how the four key dimensions – learner characteristics, educational context, LMS component engagement, and learning outcomes – interact across student subpopulations. The results highlight the importance of considering both individual characteristics (like prior knowledge and self-regulation skills) and contextual factors (like time constraints and access patterns) when designing personalized learning environments.

These findings have important implications for learning analytics implementations. As Elliott and Luo (2022) demonstrated using Canvas LMS logs during the COVID-19 transition, student subgroups showed different behavioral changes when moving

online, with historically underrepresented groups using mobile devices more frequently. Our results extend these findings by showing how these behavioral differences translate into differential effectiveness of specific LMS components.

More broadly, our findings suggest a more nuanced approach to personalization in higher education – one that recognizes systematic differences between student subpopulations while acknowledging individual variation within these groups. Rather than viewing personalization as entirely individualized, this perspective suggests that certain adaptations may benefit entire subpopulations that share common characteristics and contexts. This aligns with Tetzlaff et al. (2021), who propose a dynamic framework of personalization that acknowledges both macro-level and micro-level adaptations.

Practical implications

These findings have important implications for creating more inclusive and effective Moodle course designs:

For courses serving primarily part-time students, instructors should prioritize interactive activities, particularly SCORM packages that provide self-contained learning experiences. Communication tools, especially forums that allow asynchronous interaction, should be emphasized. Assignments should provide clear structure and guidance, and explicit connections between resources and activities should be established. These design choices help compensate for the reduced face-to-face interaction that part-time students experience, providing essential scaffolding for their learning.

For courses serving primarily graduate students, comprehensive course information with clear organization should be provided. Diverse external resources (URLs) and detailed page resources should be incorporated. The quality rather than quantity of interactive activities should be emphasized, and greater autonomy in learning pathways should be allowed. These design choices leverage graduate students' more developed disciplinary knowledge and self-regulation skills, enabling them to navigate complex information landscapes more independently.

For courses serving undergraduate students, more structured interactive activities should be incorporated. More frequent, lower-stakes assessments should be provided. Supportive resources like glossaries should be included, and communication tools that build community should be emphasized. These design choices provide the additional scaffolding that undergraduate students typically need as they develop disciplinary knowledge and academic skills.

For courses serving mixed student populations, a balanced component mix should be maintained. Multiple assessment types should be provided. Clear, consistent course organization should be ensured. Structured communication opportunities should be incorporated, and activities should be scaffolded with increasing complexity. These design choices support diverse student needs within a unified course structure, promoting more equitable outcomes across subpopulations.

These design recommendations move beyond generic “best practices” to address the specific needs of different student subpopulations, supporting more personalized and equitable learning experiences in higher education.

Limitations and future research directions

This study has several limitations that suggest directions for future research. First, the data comes from a single Ukrainian university during a specific time period (2020–2022), which included pandemic disruptions. Future research should examine these patterns across different institutional and cultural contexts to assess the generalizability of our findings.

Second, our analysis focused on form of education and educational level, but other demographic variables (age, prior education, technological proficiency) likely influence how students engage with Moodle components. Future studies should incorporate a broader range of student characteristics to develop more comprehensive models of differential effects.

Third, while we examined grade distributions, we did not have access to individual student engagement data. Future research using learning analytics at the individual student level could provide more granular insights into personalization effects. This approach could help bridge the gap between subpopulation-level patterns and individual learning trajectories, supporting more targeted personalization strategies.

Fourth, our study provides a snapshot rather than tracking changes over time. Longitudinal studies examining how the effectiveness of different components evolves as students progress would be valuable. Such research could reveal how personalization needs change as students develop greater digital literacy and self-regulation skills.

Finally, despite using SEM-PLS, our ability to make causal claims is limited by the observational nature of the data. Future research could employ experimental designs to test the effectiveness of different design approaches for specific student populations, providing stronger evidence for causal relationships.

Future research should also explore how emerging technologies like artificial intelligence can enhance the personalization capabilities of Moodle. Recent advancements in learning analytics and adaptive technologies offer promising opportunities for more sophisticated personalization approaches that dynamically respond to individual student needs while accommodating systematic differences between student subpopulations.

Conclusion

This study demonstrates that the effectiveness of Moodle components varies significantly across student subpopulations, highlighting the importance of considering diverse student needs in course design. By identifying specific components and design patterns that benefit different student groups, we provide a foundation for more personalized and inclusive digital learning environments in higher education.

Our findings reveal clear patterns in how Moodle course designs differentially impact part-time versus full-time students and undergraduate versus graduate students. Interactive activities and communication tools show substantially stronger relationships with learning outcomes for part-time students, while comprehensive information and resources demonstrate stronger impacts for graduate students. These differences reflect the distinct educational contexts and learning characteristics of these student populations.

We also identified design patterns associated with more equitable outcomes across student subpopulations, including balanced component mix, multiple assessment types, structured communication, clear organization, and scaffolded activities. These patterns suggest that inclusive course design requires attention to both component variety and structural clarity, supporting diverse student needs within a unified course structure.

These insights contribute to both theoretical understanding and practical implementation of personalized learning in higher education. Theoretically, they extend our Differential Adaptive Effect Framework by providing empirical evidence for how learner characteristics, educational context, LMS component engagement, and learning outcomes interact across student subpopulations. Practically, they offer actionable guidance for instructors and instructional designers seeking to create more effective and inclusive Moodle courses for diverse student populations.

Author contributions

Serhiy O. Semerikov conceptualized the study, developed the differential adaptive effect framework (DAEF), and drafted the manuscript, including the introduction, theoretical framework, literature review, and conclusion. Pavlo P. Nechypurenko designed the research methodology and established the scoring rubric for evaluating course components. Tetiana A. Vakaliuk analyzed and interpreted the findings, contributing significantly to the discussion section with evidence-based recommendations for practice. Iryna S. Mintii performed the statistical analyses using structural equation modeling and enhanced the theoretical framework by mapping specific Moodle components to adaptive learning dimensions. Liliia O. Fadieieva collected and processed data from the Moodle courses, created the data visualizations, and prepared the figures and tables. All authors collaboratively reviewed, revised, and approved the final manuscript prior to submission.

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Data availability

The dataset analysed during the current study is available in the Zenodo repository, <https://doi.org/10.5281/zenodo.10938019>.

Declarations

Competing interest

The authors declare that they have no competing interest.

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