Exploring the Interplay of Moodle Tools and Student Learning Outcomes: A Composite-Based Structural Equation Modelling Approach

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Abstract. This study is dedicated to researching the interconnectedness of Moodle resources and activities and their influence on student learning outcomes. We developed a conceptual model using a quantitative structural equation modelling approach based on the social constructionist pedagogy underlying Moodle's development and the university's regulations regarding Moodle's course structure and assessment. The model is comprised of five elements: Information, Resources, Activities, Communication, and Assessment. The modelling results revealed a strong positive relationship between the Activities construct (interactive learning activities) and the Communication construct, suggesting that increased utilisation of interactive activities within Moodle courses is associated with higher levels of communication and engagement. Additionally, a moderate positive relationship was observed between the Resources and Activities construct, indicating that the availability and variety of resources within a Moodle course are linked to the inclusion of diverse learning activities. Furthermore, a moderate positive relationship was found between the Information construct (course description, syllabus, introduction) and the Assessment construct (student grades), implying that well-designed and informative course materials are associated with better student performance on assessments. Notably, the study did not find evidence of a significant direct relationship between Communication or Activities and the Assessment construct, suggesting that their impact on assessment performance is more complex and influenced by other factors. The research highlights that the mere use of Moodle tools does not guarantee the implementation of adaptive learning for students of pedagogical universities. To truly leverage the potential of adaptive learning, instructors and course designers must employ a deliberate and strategic approach, integrating appropriate pedagogical strategies and using Moodle's adaptive capabilities in alignment with specific learning objectives and student needs.

Keywords: Moodle · Structural Equation Modelling · Adaptive Learning · Pedagogical Universities · Student Learning Outcomes · Moodle Tools Interconnectedness

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1 Introduction

According to the literature review [8–10], one of the future research prospects is the development of adaptive learning systems [20] based on learning management systems (LMS) like Moodle. Osadchyi [19] outlined methods for using the LMS Moodle to enable individualisation and personalisation of education in higher education institutions. Although Moodle is not designed by its developers as an adaptive learning system, the growing popularity of adaptive learning technology has motivated Moodle developers and other programmers to enhance its capabilities in this area [19, p. 37].

According to Osadchyi [19, p. 37], the Moodle LMS provides the following tools to implement an individual approach: tools for forming the training route by imposing the necessary restrictions on the training elements (tracking the performance of the element, tracking the level of assessment); multi-criteria evaluation tools (Evaluator's Handbook, Rubrics), which consider the material's complexity; tools that allow the implementation of the multivariate presentation of educational information within the framework of a single distance course; formation of a presentation profile for each group of listener's educational material. Moodle offers several features that can support a personalised learning experience: modular course structure, variety of activities and resources, adaptive feedback and assessments, and interactive learning tools. Thus, Moodle LMS can be used as an adaptive learning system in a particular context.

Many works are devoted to learning analytics and machine learning [16] in Moodle LMS [22]. Thus, Abuzinadah et al. [4], Perez-Suay et al. [21], and Kaensar and Wongnin [15] used educational data mining methods (machine learning-based system) to predict students' academic performance. Some plugins for adaptive learning were developed in the last years (e.g., Moreno-Marco et al. [18], Krahn et al. [17]) using both supervised and unsupervised machine learning techniques (Vásquez-Bermúdez et al. [23]). Thus, recent developments add value to the statement on using Moodle LMS as an adaptive learning system.

According to [1], the learning theory underlies Moodle's development is the social constructionist pedagogy that united constructionism, social constructivism, and active learning. According to Jordan [14, p. 156], "in constructivism knowledge is constructed in the mind of the learner… When they connect what they already know… to… Activities they have experienced. Active engagement, inquiry, problem-solving and collaboration characterise this type of learning with the teacher acting as a guide, facilitator and co-explorer who encourages the students to question, challenge and formulate their own ideas, opinions and conclusions. Social constructivism a sociocultural attribute of constructivism asserts that social interaction promotes reflection, the development of communication skills, deep conceptual understanding and exposure to different ideas." The findings by Jordan [14] showed that the activities provided by Moodle do foster a constructivist approach to learning and can provide students with the types of learning experiences they desire. However, their effectiveness is, to a large extent, dependent on the teacher's role in designing and directing the online learning experience.

The relationship between learning and student outcomes, often measured through grades or marks, has been a central focus in education for centuries. Traditionally, this relationship has been conceptualised as a linear progression:

$$\text{Learning} \rightarrow \text{Assessment} \rightarrow \text{Grades/Marks}$$

This model assumes a uniform learning experience for all students, followed by a standardised assessment determining their grades. However, this simplistic approach fails to acknowledge individuals' diverse needs and learning styles, potentially hindering student engagement and ultimately affecting their performance. To address these limitations, the concept of adaptive learning has emerged, aiming to personalise the learning experience for each student. This approach can be summarised as follows:

$$\begin{aligned}&\text{Adaptive Learning} \rightarrow \text{Personalized Learning Experience}\\&\rightarrow \text{Higher Engagement} \rightarrow \text{Higher Grades/Marks}\end{aligned}$$

This model proposes that technology and data-driven insights can tailor learning environments to individual needs and preferences. By creating a personalised learning experience, students are more likely to become engaged with the material, leading to deeper understanding and, ultimately, higher grades or marks [25, 26]. In this context, Moodle is a potential platform for fostering better student outcomes through adaptive learning practices.

In Kryvyi Rih State Pedagogical University (Ukraine), the following regulations [2, 3] define the recommended Moodle course structure and grades that can be united into the five constructs:

1. **Information**: The course's full name must begin with a code that reflects the form of education (full-time, part-time) and educational level – bachelor's or master's. Also provided is the semester in which the discipline is taught and the teachers [2, p. 6, 9, 13], and course status (normative or optional academic discipline). The following data [2, p. 13–14] can be extracted from the course abstract: 1) *Form of education*, 2) *Educational level*, 3) *Semester* (1 to 8), 4) *Status*, and 5) *Number of teachers*, which together form the construct "Information".
2. **Resources**: "Mandatory elements of the course are: general information about the academic discipline [*Label*]…; information about the teacher… – in the form of the *Page* resource type; *URL* to the working program of the academic discipline… And the syllabus" [2, p. 14]. "Course may also contain:… *Books*" [2, p. 16]. Resources not regulated by the regulation but can be used in courses: *Folder* and *File*. All these 6 resources together form the construct "Resources".
3. **Activities**: "The components of the courses are mainly drawn up in the form of: *Assignment*, *Quiz*, *SCORM*, *Glossary*, *Lesson*, *Feedback*" [2, p. 16], *H5P*, *HotPot*, *Survey*, *Database*, *Choice*, *Visiting*, *Wiki*, *LTI External tool activity*, *Workshop*. All these 15 activities together form the construct "Activities".
4. **Communication**: "*Forum*, in particular, announcements (news forum) provides an announcement of events, notification of changes in course, etc.; a forum for questions to the teacher – provides communication between the teacher and students regarding problems, questions that arise during the study of the discipline" [2, p. 16]. *Chat* can also be used for this. These 2 activities form the construct "Communication".

5. **Assessment**: "The final assessment of the student's academic performance is determined on a 100-point scale, the ECTS scale and the national grading scale" [3, p. 4]. All these scales are closely connected; therefore, a 6-grade modified ETCS scale can be used: A (the highest mark), B, C, D, E (the lowest passing mark), F/FX (not passed).

According to the social constructionist pedagogy, these constructs can be closely connected: *Information* is the single entry point to each course – therefore, other constructs are connected with it; *Resources* are used by students to build understanding and to prepare for *Activities*; *Activities* are used by teachers to involve students in problem-solving, exploration, and hands-on experiences using *Communications* like online communities and group work; *Communication* fosters interactions and knowledge acquisition through discussions and collaborative projects to enhance understanding; *Assessment* measures observable outcomes and focuses on understanding how students construct knowledge and apply it in real-world contexts.

The research objective is to determine whether the use of Moodle (its resources and activities) contributes to the personalisation of learning, namely, whether the content of a course in Moodle with various resources and activities is associated with student learning outcomes. This objective can be restated in the terms defined above as follows:

1. How interconnected are the Moodle internal constructs like *Information*, *Resources*, *Activities*, and *Communication*?
2. How connected are the Moodle internal constructs (*Information*, *Resources*, *Activities*, and *Communication*) and external *Assessment* construct?

The hypotheses for the research study have been developed:

H1: There is a significant relationship between the *Information* construct and *Communication* construct in the Moodle course.
H2: There is a significant relationship between the *Communication* construct of the Moodle course and the external *Assessment* construct.
H3: There is a significant relationship between the *Resources* construct and *Activities* construct in the Moodle course.
H4: There is a significant relationship between the *Resources* construct and *Information* construct in the Moodle course.
H5: There is a significant relationship between the *Resources* construct and *Communication* construct in the Moodle course.
H6: There is a significant relationship between the *Resources* construct of the Moodle course and the external *Assessment* construct.
H7: There is a significant relationship between the *Activities* construct and *Information* construct in the Moodle course.
H8: There is a significant relationship between the *Activities* construct and *Communication* construct in the Moodle course.
H9: There is a significant relationship between the *Activities* construct of the Moodle course and the external *Assessment* construct.
H10: There is a significant relationship between the *Information* construct of the Moodle course and the external *Assessment* construct.

The remainder of this paper is structured as follows: Sect. 2 details the materials and methods used in this study, including the research design, data collection procedures, and the structural equation modelling approach. Section 3 describes the experiments conducted, including the model construction and algorithm settings. Section 4 presents the results, covering the goodness of fit of the model, measurement model parameter estimation, and structural equation modelling analysis. Section 5 discusses the findings in relation to the research questions and hypotheses. Finally, Sect. 6 concludes the paper by summarizing the key findings and their implications for using Moodle to support adaptive learning in pedagogical universities, and considers the study's limitations and future research directions.

2 Materials and Methods

2.1 Research Design and Stages

The study employed a quantitative approach to examine and test the proposed hypotheses. Specifically, the Structural Equation Modeling – Partial Least Squares (SEM-PLS) technique was utilised to create the model and investigate the strength and reliability of the relationships between the constructs. The SEM-PLS approach is a powerful statistical method that combines factor analysis and path analysis, allowing researchers to examine the relationships between multiple independent and dependent variables simultaneously [12, p. 96]. This technique is advantageous when dealing with complex models involving latent variables which cannot be directly observed or measured.

The data analysis and model estimation were performed using Adanco, a specialised software package for SEM-PLS modelling [11]. Adanco is known for its efficient and robust algorithms, enabling researchers to process large datasets quickly and accurately. This software facilitated the estimation of the model parameters, assessment of the measurement model, and evaluation of the structural model [13], thereby providing insights into the relationships among the constructs under investigation.

The research was conducted in the four stages (Table 1).

2.2 Data Collection

Data from Kryvyi Rih State Pedagogical University (KSPU) were used for the empirical analysis. The collection and digitisation of student performance data across all university specialities for the 2020–2021 (winter and summer sessions) and 2021–2022 (winter session) academic years were approved by the KSPU rector's decision and the university's ethical committee on January 26, 2024.

The Course module instances report plugin [24] was installed and used to export a spreadsheet with the course data:

- *Course name* – the original course title from the KSPU Moodle site (https://moodle.kdpu.edu.ua);
- *Course ID* – unique number (3..10062) identified the course; it can be useful for courses with identical titles;

- *Root category* – the course root category used in KSPU. Each category has been encoded with a unique number as follows: 1 – Faculty of Natural Sciences; 2 – Faculty of Psychology and Pedagogics; 3 – Faculty of Geography, Tourism and History; 4 – Faculty of Pedagogical Education; 5 – Faculty of Foreign Languages; 6 – Faculty of Arts; 7 – Faculty of Ukrainian Philology; 8 – Faculty of Physics and Mathematics; 9 – All-university departments and divisions;
- *Category* – additional course category further ignored;
- *Module types*: H5P, HotPot, SCORM, URL, Survey, Database, Choice, Visiting, Wiki, Glossary, Assignments, Feedback, LTI External tool activity, Book, Label, Workshop, Page, Folder, Quiz, Lesson, File, Forum, Chat;
- *Instances* – the number of module instances used in the course.

Table 1. Research stages.

Stage	Title	Purpose	Characteristics
1	Conceptual model development	To develop a conceptual model based on the social constructionist pedagogy underlying Moodle's development and the university's regulations regarding Moodle course structure and assessment	Five constructs were identified – Information, Resources, Activities, Communication, and Assessment. Hypothesized relationships between these constructs were established
2	Data collection	To collect data on Moodle course components and student grades from Kryvyi Rih State Pedagogical University (KSPU)	Course data was exported using the Course module instances report plugin. Student performance data was digitized from grade sheets. The data covered the 2020–2021 and 2021–2022 academic years
3	Data preparation and analysis	To prepare the collected data for analysis and conduct structural equation modelling using the SEM-PLS approach	The exported data was cleaned, and relevant courses with student grades were selected. The prepared dataset was imported into Adanco 2.4 software for SEM-PLS analysis
4	Model evaluation and interpretation	To assess the model's goodness of fit, estimate measurement model parameters, and interpret the structural equation modelling results	Various fit indices, reliability measures, and validity tests were examined. The strength and significance of relationships between constructs were evaluated based on path coefficients and bootstrap results

The total number of records received on April 07, 2024, was 25595. After receiving the list of all courses, courses with a non-educational purpose (surveys, service, etc.) and courses taught in graduate school were removed from the general list. The total number of records after removal is 17985.

The new spreadsheet was built based on the exported non-removed data [7]. The total number of courses in the spreadsheet is 3600. The information block was also added (the data were extracted manually from the course annotations in Moodle), including the form of education, educational level, semester, status, and number of teachers. After that, the relevant courses with student grades were filled in. This process was completed, and the number of courses was reduced to 985, as new courses not taught from 2020 to 2022 were excluded. Prepared dataset from 985 observations without missing values available at Zenodo [7].

3 Experiments

The prepared dataset [7] was imported in Adanco 2.4. Then, five constructs were created from indicators listed in [7] as described in Sect. 1 (Table 2).

Table 2. Composite model constructs.

Name	Type	Indicators
Information	Emergent	Form of education, Educational level, Semester, Status, Number of teachers
Resources	Emergent	Label, Page, URL, Book, Folder, File
Activities	Emergent	Assignment, Quiz, SCORM, Glossary, Lesson, Feedback, H5P, HotPot, Survey, Database, Choice, Visiting, Wiki, LTI External tool activity, Workshop
Communication	Emergent	Forum, Chat
Assessment	Latent	A, B, C, D, F

In structural equation modelling, constructs can be classified into emergent and latent. The choice between emergent and latent constructs depends on the nature of the variables. Emergent constructs, or composite or formative constructs, are formed by combining or "causing" a set of observed indicators or variables. In other words, the indicators collectively define and cause the construct. The indicators are not necessarily expected to be correlated, and the construct is a linear combination of these indicators. In Table 2, the following constructs are specified as emergent: Information, Resources, Activities, and Communication. The choice of emergent type for these constructs is appropriate because the indicators are assumed to define or cause the construct rather than being manifestations or effects of the construct.

Latent or reflective constructs are unobserved or unmeasured variables that are assumed to cause or influence a set of observed indicators or variables. In Table 2, the Assessment construct is specified as latent. A latent type for the Assessment construct is appropriate because the indicators (A, B, C, D, F) are assumed to be reflections or manifestations of the underlying assessment construct. In other words, the Assessment construct is assumed to cause or influence the observed indicators.

The source of indicators for emergent constructs is the data exported directly from Moodle (observed in Moodle). The source of indicators for latent construct is the students' performance data digitised from the grade sheets (unobserved in Moodle). Emergent constructs are formed by the combination of indicators observed in Moodle, while latent construct is assumed to cause or influence the observed indicators.

The last step was setting the linear relationship between constructs according to the hypothesis (Fig. 1, Table "Design Matrix" [6]).

4 Results

4.1 The Goodness of Fit of Model

Table "Overall Model" [6] contains goodness-of-fit statistics for the model.

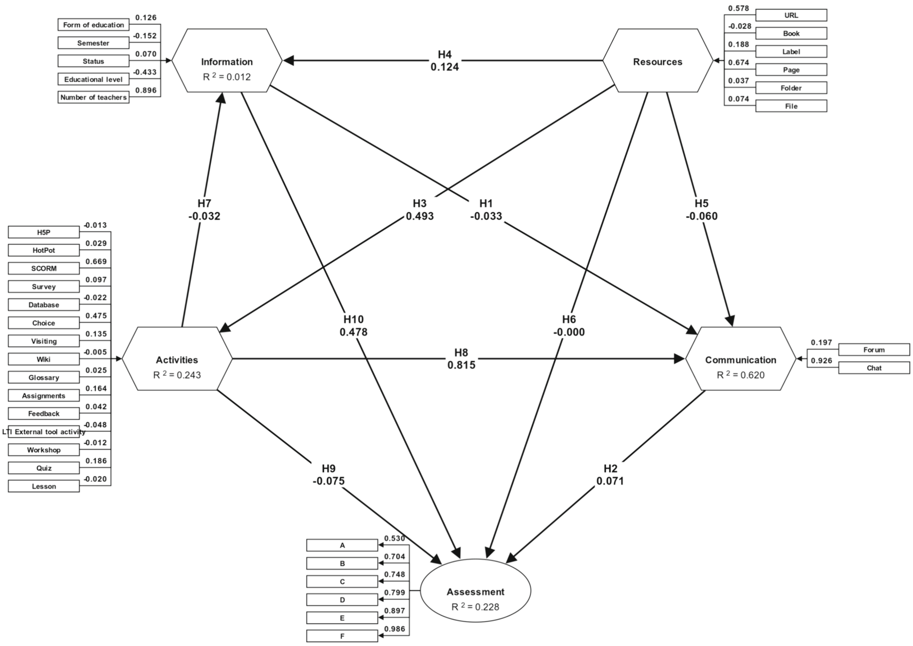

Fig. 1. Conceptual model in Adanco 2.4.

The standardised root mean squared residual *SRMR* measures the discrepancy between the observed correlations and those predicted by the model. A low SRMR (0.0546) indicates a good fit.

Unweighted least squares distance d_{ULS} measures the discrepancy between the observed and reproduced pairwise distances among the samples. It reflects how well the model reproduces the distances between the samples. A low value (1.7755) indicates a good fit.

Geodesic discrepancy d_G is another approach to quantify how strongly the empirical correlation matrix differs from the model-implied correlation matrix. The low value (0.8083) indicates a good fit.

HI95 (95% highest density interval) and HI99 (99% highest density interval) provide uncertainty intervals. The calculated values are less than the respective HI95 values for all tests. This suggests that the model provides a good fit to the data, as the fit statistics are within an acceptable range, considering the uncertainty in their estimates.

4.2 Measurement Model Parameter Estimation

Dijkstra-Henseler's rho (ρ_A) measures the internal consistency reliability of the constructs in your model. It ranges from 0 to 1, where higher values indicate greater reliability. In our case, ρ_A for the Assessment construct (the only construct with latent variables) is 0.9267, suggesting a high internal consistency level among the items measuring by construct: the number of grade marks A, B, C, D, E, F/Fx, respectively.

Jöreskog's rho (Dillon-Goldstein's ρ), or composite reliability (ρ_c), measures internal consistency reliability of sum scores. A value closer to 1 indicates higher reliability. In our case, ρ_c is 0.9063, indicating good internal consistency among the items.

Cronbach's alpha (α) is a lower bound estimate of the reliability of sum scores. Like the previous measures, it ranges from 0 to 1, with higher values indicating greater reliability. Our α value is 0.9122, suggesting high internal consistency among the items.

The average variance extracted (AVE) equals the average indicator reliability. The AVE is typically interpreted as a measure of unidimensionality. It ranges from 0 to 1, where higher values indicate that the indicators account for a larger proportion of the variance in the constructs. An AVE value of 0.6252 indicates that, on average, around 62.52% of the constructs' variance is captured by their respective indicators. The AVE value is greater than 0.5, indicating good convergent validity. The diagonal AVE (Table "Discriminant Validity: Fornell-Larcker Criterion" [6]) is greater than other correlation coefficient values in the matrix, indicating excellent discriminant validity.

Table "Loadings" [6] presents factor loadings for indicators across five constructs: Information, Resource, Activities, Communication, and Assessment. Factor loadings indicate the strength and direction of the relationship between an indicator and its corresponding construct.

Educational level has a moderate negative loading (−0.3894), indicating an inverse relationship with the Information construct. According to the selected encoding for this indicator (see [7] for details), the Moodle courses for bachelor students are better described in their introductions and syllabuses than for master students. In the Information construct, indicators like the Number of teachers contribute significantly (0.9158), while others like Semester or Status have a relatively minor impact on the construct. In the Resource construct, URLs, Labels, and Pages play significant roles, while indicators like Books or Folders have a relatively minor effect on the construct. In the Activities construct, activities like SCORM, Choice, and Assignments play a significant role; others, like H5P or Workshops, have a relatively minor impact. Chat activities notably contribute significantly to the Communication construct, while Forums also play a substantial role in facilitating communication among learners and instructors.

In the Assessment construct, all indicators contribute significantly, with indicators like F (0.9863) playing a particularly prominent role in evaluating learner performance. To assess the indicator reliability, the squared standardised loadings were calculated. Indicator F (lowest grade/fail) has an extremely high reliability of 0.9728 in measuring the Assessment construct. This suggests that a failing grade is a reliable indicator of poor assessment performance. Indicator E (low grade) also has a high reliability of 0.8041, meaning lower grades are reliable indicators of poorer assessment outcomes. As the grades improve from D (0.6377) to C (0.5602) to B (0.4954), the indicator reliability decreases. This implies that higher grades become less reliable measures of the Assessment construct. Indicator A (highest grade/pass) has the lowest reliability of 0.2812. A high/passing grade is not a reliable indicator of the Assessment construct, likely because the construct encompasses a range of assessment outcomes, not just the highest level of performance. In this context, the reliability values align with the expectation that lower grades are more reliable indicators of poor assessment performance. In comparison, higher grades are less reliable indicators of the overall Assessment construct, which includes a range of performance levels.

Indicator loadings represent the correlation between each indicator and its respective construct, while indicator weights (Table "Weights" [6]) represent the contribution of each indicator to its respective construct. The weights and indicator loadings are consistent and positively correlated, indicating the model's robustness. As the Assessment construct is latent, its indicator loadings are placed in the conceptual model. As all constructs except the Assessment are emergent, their weights are placed in the conceptual model (Fig. 1).

The cross-loadings table shows the correlations between each indicator variable and the composite model constructs. To assess the discriminant validity of the measurement model, we should examine whether each indicator loads highest on its intended construct. Based on Table "Cross Loadings" [6], all indicators load highest on their intended constructs. High positive cross-loading values (above 0.3) indicate that the indicator is strongly associated with the indicated construct. Low positive values (around 0.1 to 0.3) indicate a moderate association between the indicator and the construct. Values close to zero (around 0.0) suggest the indicator is weakly associated with that construct and may not be a good measure. Removing indicators with consistently low loadings (close to zero or at least less than 0.1) is generally recommended across all constructs. Therefore, the following indicators can be removed: Semester, Status, H5P, HotPot, Wiki, Book, LTI External tool activity, Workshop, and File. This can mean that factors such as the Semester in which the course is touched and the course Status (normative or optional) are insufficient in this model. Excepting File, the other indicators are rare in the courses: 3 H5P activities contain only course ID 3314, 3 HotPot activities contain only course ID 182, 24 Wiki activities are in 4 courses of 985, 75 Book resources are in 24 courses of 985, 1 LTI External tool activity in only course ID 4248, 73 Workshop activities are in 8 courses of 985.

Table "Indicator Multicollinearity" [6] shows the values for indicator multicollinearity (variance inflation factor – VIF). Multicollinearity occurs when two or more predictors in a regression model are highly correlated. For emergent constructs, multicollinearity may affect the indicator weights [11, p. 28].

VIF values can be interpreted as follows:

1. Values close to 1 (around 1.00 to 1.20) indicate a very weak or no multicollinearity issue. Most indicators in the model fall under this category, including those for Information (except Semester at 1.2950), Resources, Communication (both indicators have the same value of 1.0883), and most Activities (except Choice, Assignments, and Glossary).
2. Values between 1.2 and 5 indicate a moderate level of multicollinearity. In the given model, Semester and Educational level (Information), Choice (1.7799), Assignments (1.8277), Glossary (Activities), and Assessment indicator F (1.7761) fall into this range.
3. Values above 5 indicate a high degree of multicollinearity, which can be problematic for the model. Assessment indicator D (5.8080) fall into this range.

Generally, a value below 5 for an indicator is considered acceptable, while a value above 5 indicates potential multicollinearity issues. However, some researchers suggest more conservative thresholds, such as 3.3 or lower. In the Assessment construct, the indicators C (4.8197), D (5.8080), and B (3.7548) have values above the conservative threshold of 3.3, suggesting potential multicollinearity concerns among these indicators. The indicators A (1.9784), E (3.2687), and F (1.7761) are within acceptable ranges. While most constructs show no significant multicollinearity issues, the Assessment construct exhibits potential concerns, particularly among the indicators C, D, and B. The Activities construct also has two indicators (Choice and Assignments) with slightly elevated values, but not as severe as the Assessment construct. All concerned indicators have strong positive and very strong positive loadings on their intended construct, so they cannot be removed to reduce redundancy and multicollinearity issues. Specifically, the high VIF values for B, C, D, and E suggest that these grade indicators are highly correlated, meaning they measure or represent a similar underlying construct (in this case, student performance or achievement). For example, suppose students score a high grade (e.g., A or B) in one assessment component. They will likely score similarly high in other components, leading to a strong correlation among the grade indicators. Similarly, students who score low grades (e.g., D or F) in one component are likelier to score low grades in other components, contributing to multicollinearity.

Therefore, we decided to investigate multicollinearity among the different grades in depth. We divided the Assessment construct into up to 6 constructs with different grade combinations. The updated model contains four lateral constructs instead of one related to the following grades: construct A contains indicator A only with VIF = 1.0000, which indicates no multicollinearity issue; construct B contains indicator B only with VIF = 1.0000, which indicates no multicollinearity issue; construct C, D contain indicators B and C with VIF = 4.1927, indicating a moderate multicollinearity level; construct E, F contains indicators E and F with VIF = 1.7334, indicating a moderate multicollinearity level. This probably indicates the real 4-grade scale used by teachers in KSPU, which corresponds to the shifted national scale: A is an excellent mark, B is a good mark, C and D can be satisfied marks, and E and F are failing marks. Moreover, the KSPU teachers are most uneven in their assessment when marks are C and D. Moreover, it was impossible to build a model with a separate E grade: a review of digitised students' performance data shows that most E marks correspond to only one mark – 50 (the bottom level of the E mark according to the KSPU scale). In this regard, eliminating other scales used to assess students in KSPU besides the 4-grade national scale seems to be a good idea.

5 Discussion

5.1 Structural Equation Modelling Analysis

The coefficient of determination (R^2) represents the proportion of variance in the observed data that the model can explain. The adjusted coefficient of determination ($\overline{R}^2$) is a modification of the R^2 that takes the sample size into account and compensates for the independent variables added to the model (Table "R-Squared" [6]). The Communication construct has the highest R^2 and $\overline{R}^2$ values, suggesting a relatively good fit of the model for this construct. The Activities and Assessment constructs have moderate explanatory power. In contrast, the Information construct has a relatively low R^2 value, indicating that its indicators may not adequately explain the variance in this construct.

The regression coefficient, which consists of the coefficients of direct (path coefficient) and indirect effects, is used to confirm or refute the hypotheses.

Consider the influence of direct effects (direct path coefficient) in Table "Path Coefficients" [6]. The path coefficients are standardised regression coefficients (beta values) shown in Fig. 1 on the arrows between constructs. A path coefficient quantifies the direct effect of an independent variable on a dependent variable. Path coefficients are interpreted as the increase in the dependent variable if the independent variable were increased by one standard deviation and all the other independent variables in the equation remained constant [11]. Interpretation of Table "Path Coefficients" [6] results:

– **Information on Assessment**: There seems to be a positive and relatively strong effect ($\beta_{10} = 0.4785$) of Information on Assessment. This suggests that the better-described course leads to increased Assessment.
– **Activities on Assessment**: Activities have a negative effect ($\beta_9 = -0.0755$) on Assessment. An increase in Activities might lead to a slight decrease in Assessment scores, but the effect is weak.
– **Activities on Communication**: Activities have a strong positive effect ($\beta_8 = 0.8152$) on Communication. This means that more Activities are associated with increased Communication.
– **Resources on Information**: Resources have a positive but weak effect ($\beta_4 = 0.1239$) on Information. An increase in Resources might lead to a slightly better-described course.
– **Resources on Activities**: There's a moderate positive effect ($\beta_3 = 0.4928$) of Resources on Activities. More Resources are associated with an increase in Activities.
– **Resources on Communication**: The effect of Resources on Communication is negative ($\beta_5 = -0.0598$) but weak. An increase in Resources might lead to a slight decrease in Communication.
– **Communication on Assessment**: The effect of Communication on Assessment is positive but weak ($\beta_2 = 0.0715$). An increase in Communication might lead to a slight increase in Assessment.

- **Activities on Information**: There's a weak negative effect ($\beta_7 = -0.0321$) of Activities on Information. An increase in Activities might lead to a slightly worse-describe course. However, the magnitude of this effect is very small.
- **Resources on Assessment**: The effect of Resources on Assessment is negative ($\beta_6 = -0.0005$) but very weak. Therefore, it can be neglected.

In addition to direct effects, indirect effects were also calculated. An indirect effect occurs when an independent variable influences a dependent variable through one or more intervening variables. The indirect effects are related to all possible paths between the constructs. Therefore, to calculate indirect effects, we should multiply the related betas (Table "Indirect Effects" [6]): Information through Communication on Assessment: $\beta_1 \cdot \beta_2$; Resources through Activities on Information: $\beta_3 \cdot \beta_7$; Resources through Activities on Communication: $\beta_3 \cdot \beta_8$; Resources through Activities on Assessment: $\beta_3 \cdot \beta_9$; Resources through Activities through Information on Communication: $\beta_3 \cdot \beta_7 \cdot \beta_1$; Resources through Activities through Information on Assessment: $\beta_3 \cdot \beta_7 \cdot \beta_{10}$; Resources through Activities through Communication on Assessment: $\beta_3 \cdot \beta_8 \cdot \beta_2$; Resources through Activities through Information through Communication on Assessment: $\beta_3 \cdot \beta_7 \cdot \beta_1 \cdot \beta_2$; Resources through Information on Assessment: $\beta_4 \cdot \beta_{10}$; Resources through Information on Communication: $\beta_4 \cdot \beta_1$; Resources through Information through Communication on Assessment: $\beta_4 \cdot \beta_1 \cdot \beta_2$; Resources through Communication on Assessment: $\beta_5 \cdot \beta_2$; Activities through Information on Communication: $\beta_7 \cdot \beta_1$; Activities through Information on Assessment: $\beta_7 \cdot \beta_{10}$; Activities through Information through Communication on Assessment: $\beta_7 \cdot \beta_1 \cdot \beta_2$; Activities through Communication on Assessment: $\beta_8 \cdot \beta_2$. All indirect effects (except the effect of Resources on Communication, which equals 0.3981) show a weak positive or negative effect. This suggests a minimal indirect influence. However, there is a strong positive indirect effect ($\beta_3 \cdot \beta_7 \cdot \beta_1 = 0.3981$) of Resources on Communication. This suggests a substantial indirect influence, possibly through other variables, that increases Communication as Resources increase.

The sum of direct and indirect effects is the total effects (Table "Total Effects" [6]): Information on Communication: β_1; Communication on Assessment: β_2; Resources on Activities: β_3; Resources on Information: $\beta_4 + \beta_3 \cdot \beta_7$; Resources on Communication: $\beta_5 + \beta_3 \cdot \beta_8 + \beta_3 \cdot \beta_7 \cdot \beta_1 + \beta_4 \cdot \beta_1$; Activities on Information: β_7; Resources on Assessment: $\beta_6 + \beta_3 \cdot \beta_9 + \beta_3 \cdot \beta_7 \cdot \beta_{10} + \beta_3 \cdot \beta_8 \cdot \beta_2 + \beta_3 \cdot \beta_7 \cdot \beta_1 \cdot \beta_2 + \beta_4 \cdot \beta_{10} + \beta_4 \cdot \beta_1 \cdot \beta_2 + \beta_5 \cdot \beta_2$; Activities on Communication: $\beta_8 + \beta_7 \cdot \beta_1$; Activities on Assessment: $\beta_9 + \beta_7 \cdot \beta_{10} + \beta_7 \cdot \beta_1 \cdot \beta_2 + \beta_8 \cdot \beta_2$; Information on Assessment: $\beta_{10} + \beta_1 \cdot \beta_2$. Comparing direct effects (Table "Path Coefficients" [6]) and total effects (Table "Total Effects" [6]), we can conclude that the strength of the effects has almost not changed, except for the influence of Resources on Communication, since there is a strong indirect effect.

The overview of effects related to hypotheses is presented in Table 3.

Table 3 contains Cohen's f^2, which indicates how substantial a direct effect is and its interpretation according to Cohen [5, p. 477–478]. After it analysing, we can select the strongest effects: H8 (Activities on Communication) has the strongest overall effect (0.8163) with a strong effect size (1.3232), indicating a substantial positive influence of Activities on Communication; H3 (Resources on Activities) has a strong positive total effect (0.4928) with a moderate effect size (0.3208), suggesting a significant impact of Resources on Activities; H10 (Information on Assessment) has a moderate positive total

Table 3. Effect overview.

Hypothesys	Effects			Cohen's f^2	Interpretation
	Direct	Indirect	Total		
H1	−0.0334		−0.0334	0.0029	unsubstantial effect
H2	0.0715		0.0715	0.0025	unsubstantial effect
H3	0.4928		0.4928	0.3208	moderate effect
H4	0.1239	−0.0158	0.1081	0.0118	unsubstantial effect
H5	−0.0598	0.3981	0.3383	0.0071	unsubstantial effect
H6	−0.0005	0.0387	0.0383	0.0000	unsubstantial effect
H7	−0.0321		−0.0321	0.0008	unsubstantial effect
H8	0.8152	0.0011	0.8163	1.3232	strong effect
H9	−0.0755	0.0430	−0.0325	0.0024	unsubstantial effect
H10	0.4785	−0.0024	0.4761	0.2920	moderate effect

effect (0.4761) with a moderate effect size (0.2920), indicating a notable influence of Information on Assessment; H5 (Resources on Communication) has a strong positive total effect (0.3383) with an unsubstantial effect size (0.0071) due to the prevailing indirect effects.

The inter-construct correlation matrix contains the estimated correlations between constructs. Results presented in Table "Inter-Construct Correlations" [6] agree with the results in Table 3. Activities and Communication (H8) have a strong positive correlation (0.7848). This indicates that these two constructs tend to increase together in the model. Resources (H3) show a moderate positive correlation with Activities (0.4928). Information and Assessment (H10) have a moderate positive correlation (0.4751). There is a positive association between Information and Assessment.

The final decision on the particular hypothesis's acceptance or rejection should be based on the total effects inference (Table "Total Effects Inference" [6]).

H1: The effect of Information on Communication is not statistically significant (p-value = 0.0802). The 95% confidence interval for the coefficient includes zero (−0.1033 to − 0.0037).
H2: The effect of Communication on Assessment is not statistically significant (p-value = 0.1545). The 95% confidence interval for the coefficient includes zero (−0.0981 to 0.3452).
H3: Resources have a significant positive effect on Activities (p-value ≈ 0). The 95% confidence interval for the coefficient is 0.2948 to 0.6763.
H4: Resources have a significant positive effect on Information (p-value = 0.0277). The 95% confidence interval for the coefficient is −0.0047 to 0.2418.
H5: Resources have a significant positive effect on Communication (p-value ≈ 0). The 95% confidence interval for the coefficient is 0.1573 to 0.5122.

H6: The effect of Resources on Assessment is not statistically significant (p-value = 0.2033). The 95% confidence interval for the coefficient includes zero (−0.0433 to 0.1150).
H7: The effect of Activities on Information is not statistically significant (p-value = 0.4033). The 95% confidence interval for the coefficient includes zero (−0.1268 to 0.0902).
H8: Activities have a significant positive effect on Communication (p-value ≈ 0). The 95% confidence interval for the coefficient is 0.1241 to 1.0329.
H9: The effect of Activities on Assessment is not statistically significant (p-value = 0.3219). The 95% confidence interval for the coefficient includes zero (−0.1097 to 0.0765).
H10: Information has a significant positive effect on Assessment (p-value ≈ 0). The 95% confidence interval for the coefficient is 0.2599 to 0.5860.

Based on the total effects inference (Table "Total Effects Inference" [6]) we accepted the hypothesis H3, H4, H5, H8, and H10. Using total effects interpretation (Table 3), we can conclude the unsubstantial effects in H4 and H5, moderate in H3 and H10, and strong in H8. Therefore, we can conclude the following:

1. There is *insufficient evidence* to conclude whether there is a significant relationship between the Information and Communication constructs in the Moodle course.
2. There is *insufficient evidence* to conclude whether there is a significant relationship between the Communication and Assessment constructs in the Moodle course.
3. There is a **moderate positive relationship** between the Resources and Activities constructs in the Moodle course.
4. There is an **insignificant positive relationship** between the Resources and Information constructs in the Moodle course.
5. There is an **insignificant indirect positive relationship** between the Resources construct and Communication construct in the Moodle course.
6. There is *insufficient evidence* to conclude whether there is a significant relationship between the Resources construct of the Moodle course and the external Assessment constructs.
7. There is *insufficient evidence* to conclude whether there is a significant relationship between the Activities construct and Information construct in the Moodle course.
8. There is a **strong positive relationship** between the Activities construct and Communication construct in the Moodle course.
9. There is *insufficient evidence* to conclude whether there is a significant relationship between the Activities construct of the Moodle course and the external Assessment construct.
10. There is a **moderate positive relationship** between the Information construct of the Moodle course and the external Assessment construct.

Therefore, the answers to the research questions are:

1. There is a significant relationship between the resources and activities and between the activities and communication in the Moodle course.
2. There is a significant relationship between the information about the Moodle course and the student's performance, and there is no evidence of a relationship between the number of components used in the Moodle course and student performance.

6 Conclusions

We also keep in mind the additional research question: *does the use of Moodle tools guarantee the implementation of adaptive learning for students of pedagogical universities?* Based on the research findings presented, there is insufficient evidence to conclude that the mere use of Moodle tools guarantees the implementation of adaptive learning for students of pedagogical universities.

While Moodle provides tools and features that could support adaptive learning, such as personalised learning paths, adaptive content delivery, and learning analytics, the mere presence and use of these tools do not necessarily guarantee the implementation of adaptive learning. Effective adaptive learning requires careful instructional design, integration of appropriate pedagogical strategies, and the strategic use of Moodle's adaptive capabilities in alignment with specific learning objectives and student needs.

To facilitate a more effective learning experience, instructors should: 1) incorporate interactive activities (e.g., SCORM, assignments, quizzes) to increase communication and engagement; 2) provide a diverse range of resources to support various learning activities; 3) create comprehensive, transparent course information to facilitate better learning outcomes; 4) explore additional strategies to translate increased engagement and communication into improved assessment outcomes; 5) consider how resources are organized, presented, and integrated with other course components; 6) intentionally leverage Moodle's adaptive features, such as personalized learning paths and learning analytics, to inform instructional decisions.

It is important to acknowledge this study's limitations, which include the specific context in which the data were collected (a single HEI and the limited time) and the inherent limitations of the methodological approaches employed. Future research could explore additional factors that influence the relationships among the various components, such as pedagogical approaches, learner characteristics, and the specific subject domains or educational levels.

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