The Impact of Learning Design on the Mastery of Learning Outcomes in Higher Education

Blaženka Divjak
Faculty of Organization and Informatics
University of Zagreb
Varaždin, Croatia
blazenka.divjak@foi.unizg.hr

Abhinava Barthakur
University of South Australia
Adelaide, Australia
abhinava.barthakur@unisa.edu.au

Vitomir Kovanović
University of South Australia
Adelaide, Australia
vitomir.kovanovic@unisa.edu.au

Barbi Svetec
Faculty of Organization and Informatics
University of Zagreb
Varaždin, Croatia
barbi.svetec@foi.unizg.hr

Abstract

Ensuring constructive alignment between learning outcomes (LOs) and assessment design is crucial to effective learning design (LD). While previous research has explored the alignment of LOs with assessments, there is a lack of empirical studies on how assessment design influences LO mastery, particularly the relationship between formative and summative assessments. To address this gap, we conducted an empirical study within an undergraduate mathematics course. First, we evaluated the course's learning design to identify potential gaps in constructive alignment. Then, using a sample of 169 students, we analysed their assessment results to explore how LO mastery is demonstrated through formative and summative assessments. This study provides a novel learning analytics (LA) methodology by combining cognitive diagnostic models, epistemic network analysis, and social network analysis to examine LO mastery and interdependencies. Our findings reveal a strong connection between the mastery of LOs through formative and summative assessments, underscoring the importance of well-constructed LD. The practical implications suggest that LA can serve as a critical tool for quality assurance by guiding the revision of LOs and optimising LD to foster deeper student engagement and mastery of critical concepts. These insights offer actionable pathways for more targeted, student-centered teaching practices.

CCS Concepts

• **Applied computing**; • **Education**; • **Computing methodologies**; • **Machine Learning**;

Keywords

Learning outcomes, Learning analytics, Learning design, Assessment design, Assessment validity

LAK 2025, March 03–07, 2025, Dublin, Ireland

ACM ISBN 979-8-4007-0701-8/25/03
https://doi.org/10.1145/3706468.3706565

ACM Reference Format:
Blaženka Divjak, Abhinava Barthakur, Vitomir Kovanović, and Barbi Svetec. 2025. The Impact of Learning Design on the Mastery of Learning Outcomes in Higher Education. In *LAK25: The 15th International Learning Analytics and Knowledge Conference (LAK 2025), March 03–07, 2025, Dublin, Ireland*. ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3706468.3706565

1 Introduction

As music starts with composing, learning analytics (LA) starts with learning design (LD) [18]. One of the first representations of the LA cycle included learners, data, metrics and interventions as essential parts of the LA process, highlighting the importance of "closing the loop" in educational practices to ensure continuous improvement [5]. Subsequent approaches have refined this understanding by presenting the continuous improvement cycle of a course, starting with the LD phase, structured around well-defined learning outcomes (LOs) [10]. As good composition is the foundation of quality music, the soundness of LD is an essential prerequisite for reliable LA research and meaningful, practical recommendations based on it.

Central to effective LD is the concept of constructive alignment [4], a pedagogical approach that ensures alignment between LOs, teaching and learning activities (TLAs), and assessment. In this framework, formative and summative assessments serve distinct but complementary purposes. Both types of assessment are integral to constructive alignment, ensuring that students progress towards achieving the intended LOs. To ensure that the assessment is valid, it is essential to consider the relative importance of each LO and align all types of assessment with the weighted LOs [10]. This consequently also means mutual alignment of formative and summative assessment [9].

Despite the widespread use of formative and summative assessment, there is a research gap regarding the empirical relationship between the mastery of LOs demonstrated in formative assessment and the mastery of those same LOs demonstrated in summative assessment. While it is widely accepted that formative assessment plays a critical role in supporting student learning and contributing to better results in summative assessment [16], there is a need for a better understanding and empirical confirmation of the role of assessment design in the mastery of LOs, particularly in higher education contexts. Addressing this need is essential for understanding how formative assessment can be better designed and aligned to enhance student performance in summative assessment, ultimately improving the acquisition of LOs and pedagogical effectiveness. Furthermore, research on students' learning approaches applied when mastering LOs, which can be reflected in their performance in formative and summative assessments, is still lacking [25].

Against this background, we conducted an empirical study to analyse the relation between students' mastery of LOs as demonstrated in different types of assessment, as well as to identify distinct groups of students concerning their performance. To do so, we extracted students' grades from a mathematics course from a European university and analysed their mastery across seven course LOs. The contributions of this current study are twofold. The findings presented here can have valuable implications not only for further research but also for practice, supporting sound LD and enhancing students' learning performance and experiences. From a methodological standpoint, we provide a novel methodology, combining several well-established LA methods, to examine the relation of different LOs and compare the intended and executed LD.

2 Theoretical background

2.1 Learning Design

Learning design (LD) has been defined in various ways, but in essence, it presents the order of teaching and learning activities (TLAs), together with the related resources and student support [19], which are to be done by teachers and students so that the students would acquire the intended learning outcomes (LOs) [17]. It guides teachers in making informed decisions pertaining to the design of TLAs [6] but has a learner-centred nature, putting in focus the design of learning experiences corresponding with students' needs [3]. LD is planned in line with a chosen pedagogical approach [6] and attempts to increase the efficiency of teaching and learning [3]. As a contemporary practice, it highlights the use of technology, including good practice sharing through online repositories [3].

The LD approach used in this study is the research-based and innovative Balanced Design Planning (BDP) approach [7]. Such an approach is firmly based on constructive alignment [4] between LOs, TLAs and corresponding (formative and summative) assessments. It pays special attention to student-centeredness, which is especially reflected in the focus on LOs, student workload and support for applying innovative pedagogies. The BDP approach considers the prioritisation of LOs by assigning LOs with relative weights [8, 10] and enables detailed design analytics, including comparison of designed assessment per LO with the established LOs' relative weights, supporting assessment validity [10].

2.2 Formative and Summative Assessment

Meaningfully planned and implemented assessment is essential, on the one hand, for reporting on student progress and, on the other hand, for supporting and steering students' learning processes and teachers' informed decision-making [22]. With this in mind, assessment programs can include two types of assessment: formative and summative. While formative assessment means collecting data to improve students' learning, summative assessment refers to using data to assess students' knowledge once they complete a learning sequence. [13, 20] Therefore, formative assessment is done continuously throughout a learning unit, helping steer teaching and learning towards achieving LOs. In contrast, summative assessment is used to assess the achievement of LOs at the end of a learning unit. Even though there is a distinction, it has been pointed out [22] that 'formative' and 'summative' are not separate worlds in reality, as the two types of assessment are mutually closely connected. Some previous research pointed to the importance of cohesion and alignment between formative and summative assessment [12]. However, there is a lack of empirical research examining this alignment between formative and summative assessment in the context of LO mastery.

2.3 Validity of Assessment

Validity is an essential aspect of assessment, which primarily relates to the relationship between test *content* and content *standards*, with the evaluation of their mutual link being at the centre of the *alignment* process [20]. In educational terminology, the said standards are referred to as *LOs*, and the alignment between LOs and assessment has been described as *constructive alignment* [4]. To ensure the validity of an assessment program, it is crucial to align it with the intended LOs, i.e. link all assessment tasks to the intended LOs.

To support this, a model based on LA that includes a comparison between ideal LO weights, actual assessment weights (maximum assessment points per LO), and student assessment results (actually obtained assessment points per LO) has been presented [10]. It was also shown that checking assessment validity using LA is part of a continuous improvement cycle of a course, i.e., closing the loop of quality assurance. Assessment validity is one of the five criteria (reliability, validity, educational impact, acceptability, and the costs of assessment) considered in Van der Vleuten's utility formula of assessment [27].

2.4 Approaches to Learning

The concept of an approach to learning (as introduced by Marton and Saljo in 1984) includes two main categories: *deep* and *surface* learning. The former includes the intention of a student to understand the material, which requires an interaction with the content and linking it with prior knowledge and experience, inspection of evidence and evaluation of the logical steps used to draw conclusions. Conversely, the latter includes only an intention to respond to the requirements of a task or a course, which are seen as external and primarily unrelated to personal interests; this approach focuses on memorising the elements that are expected to be assessed. There is also a third approach, *strategic* (as identified by Ramsden in 1981), in which deep and surface approaches are used as needed to get the highest grades [14]. To this end, we are interested in investigating students' learning approaches to mastering different course LOs demonstrated through formative and summative assessments.

3 Methodology

To address the identified research gaps, we conducted an empirical study based on the following research questions (RQs):

RQ1: *What is the role of learning design in ensuring the mastery of LOs?* To answer this question, we analysed how the mastery of LOs demonstrated through formative assessment relates to the mastery of the same LOs demonstrated through summative assessment. Moreover, we explored the interdependencies associated with the mastery of different LOs. Here, we discuss the elements of the quality of LD and their relation to the mastery of LOs.

RQ2: *What groups of learners can be identified based on their mastery of LOs?* To answer this question, we clustered students and analysed their characteristics based on their LO mastery, as demonstrated through formative and summative assessments.

3.1 Study Setting

The study was conducted at a the University of Zagreb, Faculty of Organization and Informatics, a higher education institution delivering undergraduate and graduate study programs in ICT, particularly within a first-year undergraduate-level mathematics course (Mathematics 2) in the academic year 2023/2024. The student workload assigned to the course amounts to 6 ECTS (European Credit Transfer and Accumulation System) credits, which equals about 180 hours of students' overall workload.

The assessment program includes weekly quizzes and exercises (formative assessment), three periodical exams and a problem-solving task resulting in a mathematical essay (summative assessment). There are eight overarching LOs, and the course LD is based on weighted LOs [10], with weights assigned using the *standard* approach presented by Divjak et al. [11] (Table 1). The course LD has been prepared in the BDP tool (learning-design.eu) [7] and shared with students.

Topics cover an introduction to mathematical analysis: real functions of one real variable, sequences and series, limits of a function, derivative of a real function with applications and undefined and defined integrals with applications.

Around 400 students enrol into the course annually; most are full-time students, and a certain percentage of students retake the course because they did not pass it the previous year. There are three professors, each lecturing one lecturing group, and six teaching assistants in charge of 10 seminar groups. This study focused on one lecturing group, including 169 students. Due to the large number of students and nine teachers, having a clear, common LD framework is essential.

A constructivist approach and student-centred teaching and learning have been maintained. The course is delivered in hybrid mode, with most students attending classes face-to-face. Predominant teaching and learning approaches are flipped classroom, problem-based learning, and guided practice.

Formative tasks are individual for each student, including exercises and quizzes. Exercises include computational tasks assigned to students by random selection from the assignments database on Moodle, prepared by the course teachers. Unlike the exercises, quizzes are focused on understanding concepts, basic terminology, and solving tasks that help students comprehend the concept. They are often related to the videos given to students before lectures (flipped classroom approach) to cover basics or to recollect some mathematics from previous education. The quizzes present automated formative assessment with an automated grading system and feedback. Altogether, for the continuous weekly assignments, students can get a maximum of 30 points out of 100 points for the entire course. In reality, deviations from the LD are possible, as presented in Table 1, indicating that in the academic year of 2023/2024, the total number of assessment points was 101, with one additional point coming from an extra quiz. The weekly formative assignments serve to prepare students for their exams.

Regarding summative assessment, exams are taken three times per semester, and each contributes to the final grade with a maximum of 20 points. Each exam comprises several combined tasks, including theoretical questions and computational, practical exercises and problems. Students need to calculate and derive the final solution step by step. Students can use tools in the calculation but should provide a theoretical explanation of the procedures and results of the computational tasks. Relatively large databases (several thousands of assessment items) are used, with exercises and questions for formative and summative assessment. The exercises in the databases are classified according to the mathematical topic and three difficulty levels. Based on that, a student gets an individual exercise randomly chosen from a specific task category that usually contains between 50 and 500 different, even though similar exercises. Most of these categories have been populated with automatically generated tasks programmed in Python and R. To a certain extent, this prevents copying the results and cheating on exams. More details on e-assessment and students' perspectives can be found in [12].

Another summative task is the problem-solving essay, which is optional but can contribute 10% to the total grade. The problem-solving essay is directly related to the following course LO: Analyse and solve a moderately complex problem in the field of mathematical analysis and present the solution in the form of a mathematical essay.

The LD of the course is planned with particular attention paid to the quality of LD, including constructive alignment between LOs and assessment, and ensuring assessment validity by considering the alignment of assessment points per LO with the prioritisation (weight) of a particular LO, which is also appropriately reflected in student workload. Table 1 demonstrates the weight of each LO compared to the related assessment plan (points), actual assessment (points), average student achievement (percentage) and student workload (percentage). Moreover, Figure 1 shows the constructive alignment of LO weights with assessment and student workload as an essential element of ensuring the quality of LD.

3.2 Data Preparation

In the first phase of data preparation, we mapped all the (formative and summative) assessment items (exam tasks, quizzes and exercises) to the eight course LOs. As only the problem-solving essay was linked to the final LO (LO 8), we excluded the problem-solving essay and the related LO from the analysis and focused on the remaining seven LOs.

We split the mapping into two components: one focused on formative assessment items and the other on summative assessment items linked to the seven LOs. It is important to note that for further analysis, we only considered the presence or absence of

Table 1: Learning outcomes with weights, assessment, and workload

Learning outcomes	Weight of LO	Workload (percent)	Assessment plan - LD (points)	Actual assessment - delivery (points)	Average student achievement (percent)	Formative questions(total number)	Summative questions(total number)
LO1 Describe an elementary real function of a real variable, list its properties and sketch its graph	10	7	10	9.5	70%	2	3
LO2 Use elementary functions and their properties to solve simple real-world problems	10	10	11	11	54%	4	3
LO3 Apply sequences, series and function limits to standard tasks and mathematical problems related to informatics	19	19	19	20	45%	3	6
LO4 Explain the concept of the derivative of a real function, its geometric interpretation, and the link to continuous functions	14	13	16	13.5	61%	5	4
LO5 Apply the derivative of a function to local and global extrema of a function of one variable and the points of inflection of a function	9	8	9	8	55%	3	2
LO6 Analyse an elementary function and sketch a graph	12	13	12	11.5	48%	2	4
LO7 Determine the antiderivative of a function and apply integrals to calculate areas	16	19	13	17.5	60%	5	5
LO8 Analyze and solve a moderately complex problem in the field of mathematical analysis and present the solution in the form of a mathematical essay	10	11	10	10	68%	0	1
TOTAL	100	100	100	101		24	30

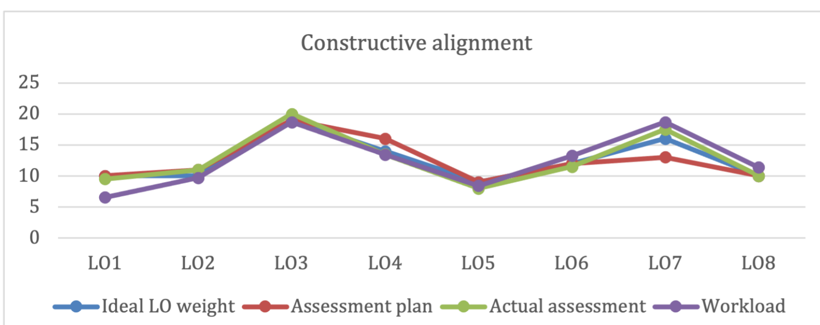

Figure 1: Constructive alignment of LOs with assessment and workload.

a link between the different assessment items and respective LOs (binary mapping) and not the actual assessment points.

In the second phase of data preparation, we obtained the assessment data from the Moodle LMS, which was related to each part of the course assessment program, i.e., each assessment item. As students were divided into three lecturing groups (divided further into 10 seminar groups), and there were fluctuations of students between the groups, to ensure consistency, in this study, we focused on the students from only one lecturing group. The sample included only full-time students, while part-time students were excluded from the analysis due to their individualised learning pathways. Finally, the study included a total of 169 students out of the total of 400 students who took the same formative and summative assessments.

As the assessment items had differing total scores, for data analysis, we computed the percentage grade for each student based on these items. We then adjusted these assessment percentage scores into three categories—below 50% indicated the students failed the assessments (denoted by 0), between 50% and 75% indicated average performance (denoted by 1), and above 75% showed high achievement (denoted by 2). The students' assessment data were aggregated and anonymised, and their privacy protected. The study was conducted with a positive opinion of the Ethics Committee of the higher education institution.

3.3 Data Analysis

We initially applied a relatively common LA technique [1], generalised cognitive diagnostic models (CDMs), to assess the mastery of various LOs through formative and summative tasks. CDMs are psychometric models that utilise the relationship between assessment items and different underlying constructs to draw conclusions about the mastery of these constructs. We utilised the mapping between formative tasks and the LOs, as well as between summative tasks and the LOs, as the input data into two separate generalised CDMs, along with the adjusted assessment grades (0, 1, and 2). The outcomes from these models yielded a binary score of 1 or 0, indicating mastery or non-mastery of each of the seven LOs, as demonstrated through either formative or summative assessment. This analysis was implemented using the CDM library [2] in R.

To investigate our first research question and gain insight into the simultaneous mastery of various LOs, we applied Epistemic Network Analysis (ENA) [23], a widely used technique to understand the relationships between several interconnected constructs. While initially developed as a technique for understanding coded communication transcripts, ENA has since been used in educational settings to understand other constructs, such as critical thinking and learning content, collaborative learning, and study strategies. ENA entails transforming binary-coded data into a network representation, with nodes representing different constructs and weighted edges representing their co-occurrence frequency. Since the output from CDMs is the binary representation of students' mastery of different LOs, it is thus perfectly suitable for the ENA analysis.

Since it originated within the discourse analysis domain, the ENA data usually consists of historical conversation transcripts, with the co-occurrence of target constructs calculated across a small part of the conversation log, called stanza. In our analysis, each row represents students' mastery of LOs, so both conversations and stanzas consist of a single record. The ENA analysis is usually visualised using projection and network diagrams, with the former showing a two-dimensional representation of all data points and the latter showing the connectedness of constructs for a specific data point (or a group of data points). To conduct our analysis, we used the R programming language and the rENA package for ENA analysis.

To further analyse links between the LOs, we used social network analysis (SNA). SNA uses graph theory to understand links among social entities (actors denoted by nodes in a graph) and the implications of these links (edges in undirected or loops in directed graphs), with social network data consisting of at least one structural variable which is measured on a set of actors. SNA aims to identify the most critical actors in the network, with a range of measures denoting the difference in the importance (centrality) of actors. Degree centrality considers that central actors are the most active, having the highest number of links to other actors in the network. Closeness centrality focuses on the closeness of a particular actor to all other actors, considering that the actor who can rapidly interact with others is central. Betweenness centrality refers to actors who can have control of other two nonadjacent actors' interactions as they lie on the path between them. [28] Eigenvector centrality considers not only the number but also the quality of connections between actors, meaning that actors with fewer high-quality links can outrank those with a higher number of links with less important actors [21].

To respond to the second RQ, we conducted hierarchical clustering with Euclidean distance in R to identify specific learner groups based on their mastery of the seven LOs, as demonstrated through formative or summative assessment. We determined the optimal number of clusters using the widely accepted average silhouette width and the clustering dendrogram. After selecting the optimal number of clusters, we examined the resulting clusters concerning their mastery of the formative and summative LOs, as described by Barthakur et al. [2]

4 Research results

4.1 Preliminary Analysis

The analysis of the students' mastery of LOs was conducted using two CDMs. The results, summarised in Table 2 and Table 3, provide insights into the average mastery scores of the cohort across the seven LOs demonstrated through the formative and summative assessments, respectively. In these two tables, the "Average Mastery" column indicates the mean mastery score for each LO across the entire cohort, while the "Total Scores" column represents the total possible scores for each LO. The "Percentage (Mastery)" reflects the proportion of mastery relative to the total possible scores. The two tables' prefixes, F and S, before the LOs refer to formative LOs and summative LOs, respectively.

The data presented in Table 2 shows the average mastery scores achieved by the student cohort in their formative tasks. As we can see, the students were able to attain higher than 50% mastery for the first LO and the fourth LO. However, the results also revealed that the cohort displayed below-average mastery across the other LOs, indicating areas where further pedagogical support may be needed.

In contrast, Table 3 illustrates the average mastery scores achieved in the summative tasks. The data shows that the students better mastered the LOs in the summative assessments. Notably, the only LO where mastery levels remained below 50% was the LO1 in the summative assessments.

Table 2: Average mastery of learning outcomes demonstrated through formative tasks

Learning outcome	Average mastery	Total scores	Percentage (mastery)
LO 1	1.01	2.00	50.30%
LO 2	1.94	4.00	48.52%
LO 3	1.17	3.00	39.05%
LO 4	2.60	5.00	52.07%
LO 5	1.46	3.00	48.52%
LO 6	0.91	2.00	45.56%
LO 7	2.25	5.00	44.97%

Table 3: Average mastery of learning outcomes demonstrated through summative tasks

Learning outcome	Average mastery	Total scores	Percentage (mastery)
LO 1	1.24	3.00	41.42%
LO 2	1.51	3.00	50.30%
LO 3	4.88	8.00	60.95%
LO 4	2.39	4.00	59.76%
LO 5	1.29	2.00	64.50%
LO 6	2.32	4.00	57.99%
LO 7	2.99	5.00	59.76%

4.2 RQ1: Relation Between the Co-mastery of Different Learning Outcomes

The ENA analysis showed the relationships between the mastery of particular LOs, as demonstrated through formative and summative assessment results. These links are presented in the plots in Figure 2 and Figure 3.

Looking at the projection plot, we see significant variability in terms of students' mastery of different LOs. Similarly, from the position of different nodes in Figure 3 that represent formative and summative mastery of different LOs, we see that the X axis mainly distinguishes between formative assessment on one side (LOs 1, 5, 6, and 7) and summative assessment on the other (LOs 3, 4, 6 and 7). In contrast, the Y axis captures the difference between LOs 1, 2, 6 and 7 on one side and LOs 3, 4, and 7 on the other.

To further examine the connections between the mastery of different LOs, we conducted an SNA analysis on the CDM estimates of the LO mastery to identify which LOs are most central and critical to student success in the course (Figure 4). For each LO, we examined its betweenness, closeness, eigenvector and weighted degree centrality (Table 4).

We can see that summative LO4, followed by LO5, are by far the two most prominent LOs with regard to betweenness centrality. Additionally, we can notice that summative mastery of LO4 has a pivotal role in the plot (high centrality), being linked to 12 other LOs as measured by formative or summative assessments, indicating the importance of mastery of this LO. Summative LO4 is followed by Summative LO5 and LO6, which also demonstrate high centrality and are linked to 11 other nodes. Looking only at summative

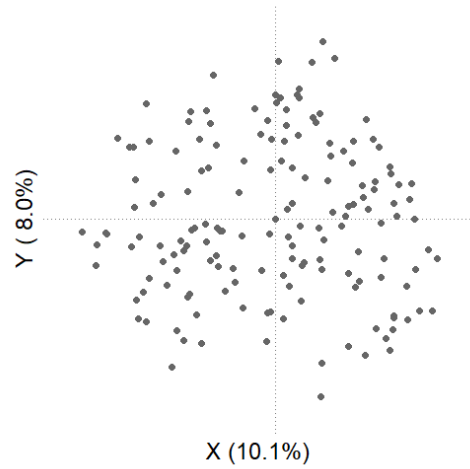

Figure 2: Two-dimensional projection showing differences between students in terms of their mastery of the different LOs demonstrated through formative (pink) and summative (green) assessments. The X and Y axis represent the two singular values that contain the most variability in the data.

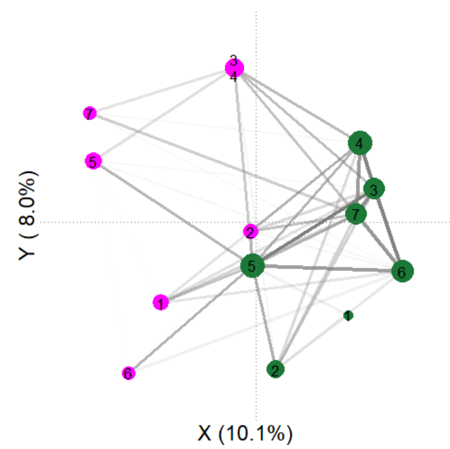

Figure 3: The relationship between the mastery of LOs demonstrated through formative and summative assessment. The strength of the relationship is indicated by the thickness of the lines, while the position of the nodes is associated with the weights of these nodes on the X and Y singular values.

assessment, the highest degree of centrality is demonstrated by LO2 and LO5, with links to the mastery of all other analysed LOs as demonstrated through summative assessment. Notably, the summative prerequisite LO1 is linked only to LO2 and LO5. Finally, from an LD perspective, we can see a clear separation between the formative LOs (left side) and the summative LOs (right side).

4.3 RQ2: Different Groups of Learners

To address RQ2, we utilised hierarchical clustering to identify distinct student groups based on their mastery of LOs, as demonstrated through formative and summative assessments. Upon analysing

Table 4: Network centrality metrics for the different LOs in the course

ID	Closeness centrality	Betweenness centrality	Eigen centrality	Weighted degree centrality
Learning outcome Formative assessment				
LO 1	0.65	0.17	0.66	0.34
LO 2	0.62	0.00	0.57	0.30
LO 3	0.50	0.00	0.12	0.05
LO 4	0.72	1.70	0.80	0.48
LO 5	0.68	0.92	0.70	0.38
LO 6	0.59	0.00	0.45	0.22
LO 7	0.57	0.00	0.45	0.22
Learning outcome Summative assessment				
LO 1	0.50	0.00	0.20	0.11
LO 2	0.68	3.50	0.70	0.41
LO 3	0.76	1.58	0.89	0.62
LO 4	0.93	17.83	1.00	0.74
LO 5	0.87	10.83	0.96	0.75
LO 6	0.87	5.83	0.99	0.68
LO 7	0.76	2.63	0.86	0.61

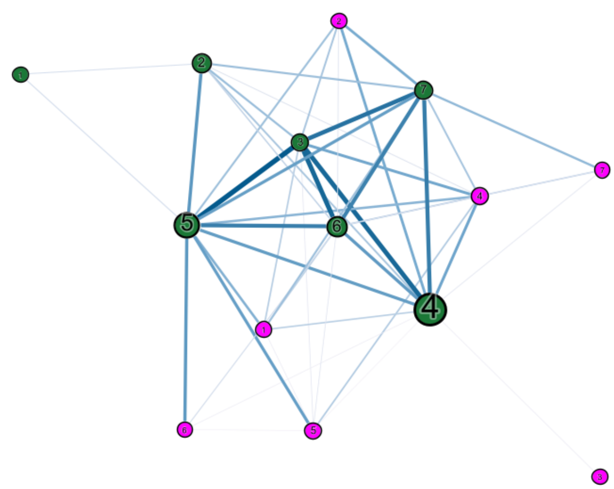

Figure 4: Social Network Analysis of the course LOs. The size of the node indicates its betweenness centrality and colour type of assessment (green - summative, pink - formative).

the clustering dendrogram (Figure 5), it became apparent that clustering solutions, including between two and five clusters, would be appropriate. While the two- and the three-cluster solutions provided generic clusters, the five-cluster solution further subdivided the students into smaller groups without adding any information. Consequently, we opted for a four-cluster solution by employing various clustering quality metrics (average silhouette width for solutions with two to five clusters are 0.15, 0.07, 0.07 and 0.05, respectively) and selecting the most informative cluster solution.

To interpret the four clusters, we analysed the students' mastery of each LO, demonstrated through formative and summative assessment, as presented in Figure 6.

High Achievers (n = 42): This cluster comprises students who consistently demonstrate high levels of mastery across both formative and summative assessments. However, mastery in specific LOs, such as summative LO1 and summative LO2, is around the average level, and notably lower mastery is observed for formative LO6. That is not surprising since mastery of LO6 requires the integration of mastery of all previous LOs and, therefore, takes more time.

Struggling Learners (n = 32): This is the smallest cluster identified in the analysis. These students consistently show low levels of mastery on both formative and summative assessments, indicating significant challenges in acquiring course LOs.

Summative-Driven (n = 55): This cluster represents the largest group of students. It is characterised by students performing better in summative than formative assessments. The average mastery rates achieved through summative assessments are higher than those observed in the High Achievers group.

Summative Underperformers (n = 40): Students in this cluster exhibited similar levels of mastery in formative assessments as the Summative-Driven Learners, with generally average mastery rates. They demonstrated exceptionally high mastery of formative LO5. This group showed a drop in performance in summative assessments, differentiating them from other groups.

5 Discussion

5.1 RQ1: What is the Role of Learning Design in Ensuring the Mastery of LOs?

In the course being analysed, it is evident that not all LOs are equally represented in terms of assessment points through formative and

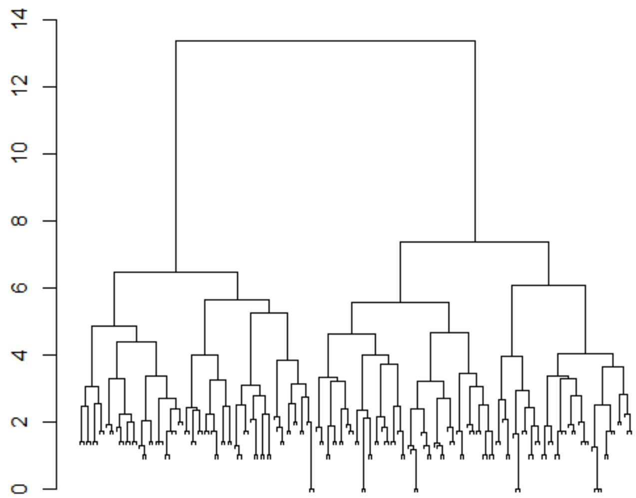

Figure 5: Clustering dendrogram.

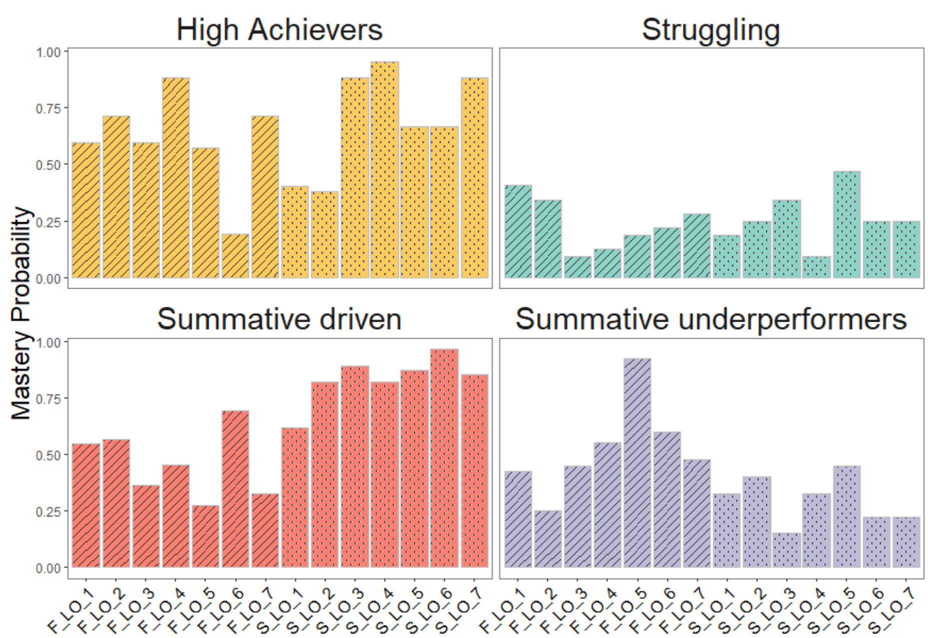

Figure 6: Student clusters representation with results per LOs (based on CDM). The F prefix and dashed bars indicate average LO mastery through formative assessments. The S prefix and the dotted bards indicate average LO mastery through summative assessments.

summative assessments (refer to Table 1). This observation underscores the deliberate prioritisation of LOs, highlighting that they do not carry the same level of importance. Consequently, these LOs do not possess identical weights, nor are they consistently covered throughout the course. Establishing LO weights and aligning the assessment program with these weights is crucial for ensuring assessment validity [8, 10].

Sound LD should be based on the principle of constructive alignment [4] between LOs, TLAs, assessment and student workload. Considering the course analysed in this study, Figure 1 shows a high level of alignment in LD between the weights of LOs, assessment points assigned to a specific LO and the corresponding student workload. Expectedly, there is a (though very slight) discrepancy between the ideal LO weights and the actual course delivery (as reflected in assessment points and student workload). Here, we have to keep in mind that the weight of an LO might be a function of several criteria, including the importance of the topic or context for the future profession, the required level of the LO based on the chosen taxonomy, contribution to the development of the 21st-century generic skills and student workload needed to fulfil the LOs [8]. Moreover, in an actual course situation, we expect some deviation from the ideal LD. This can be due to adaptation to specific student body characteristics for a particular academic year (planned 100 vs. realised 101 total assessment points; student workload associated with LO1 lower than expected due to assumed pre-knowledge), calendar and scheduling (holidays!), time constraints (LO7 having fewer assessment points than expected based on the weight), as well as more minor fluctuation due to teachers' preferences. Additionally, the cost of assessment may influence the ideal LD and an educational impact in the delivery phase can be perceived differently than in ideal assessment design. As indicated by the Van der Vleuten utility formula, it is usually impossible to fully satisfy all elements (reliability, validity, educational impact, acceptability, and assessment costs), and there are always compromises [26, 27].

Nevertheless, the validity of a course assessment program relies on the soundness of course LD and the delivery of the course that is based on the planned LD [10]. Therefore, linking formative and summative assessment with the course's intended LOs, which may be weighted, is crucial. This is demonstrated in this paper, using the example of a course in which, in LD, links between LOs and assessment were established, and assessment points were planned to correspond to the weights of the intended LOs. The second step, to ensure validity in delivery, can be affected by different factors coming from real learning environments.

Looking at the mastery of the course LOs as demonstrated separately through formative and summative assessment, in the course presented here, we found that the average mastery of a great majority of LOs demonstrated in formative assessment was lower than in summative assessment (Table 2 & Table 3). The only LO where mastery levels remained below 50% was the summative LO1, which suggests that while the overall performance improved in the summative tasks, there are still specific areas, particularly LO1, where students may require additional support to achieve better mastery.

Furthermore, the ENA analysis (Figure 3) indicated the relationship between the mastery of the LOs as demonstrated via the formative and summative assessments, showing that formative assessment of particular LOs (left side of the plot) supported the mastery of the same LO as measured by summative assessment (right side of the plot). This indicates that formative assessment provided valuable feedback to both students and teachers on their students' progress in acquiring a particular LO and to what extent, serving as a basis for further teachers' support to students and students' learning towards the acquisition of the intended LOs. Generally, this aligns with some previous research on the role of formative assessment [16], pointing out that teachers' continuous evaluation of students' development, followed by curricular modifications, made progress towards fulfilling summative assessment requirements easier and more predictable. Moreover, it supports the claims that formative information on students' comprehension, followed by teachers' timely feedback, supports students in behavioural changes, leading to more successful learning. [16] Furthermore, the findings also make sense in the context of previous studies indicating formative assessment results as strong predictors of summative assessment success [9]. Nevertheless, none of the benefits would be possible if formative and summative assessments were not mutually coherent and constructively aligned with the intended LOs.

At the same time, the ENA and SNA analyses gave us important insights into the relations between the mastery of different LOs. While such links are often chronology-related and would mostly be clear to (especially experienced) course teachers, they might provide additional evidence to support LD.

The SNA analysis showed that summative assessment stands better than formative assessment with respect to centrality metrics. This aligns with the idea of formative assessment, which is narrower in scope and supports summative assessment [9]. Particularly, LO4 is outstanding concerning all centrality metrics, especially the betweenness metric, both among summative and formative assessments. This suggests that LO4 has a central role in the course. This does not come as a surprise, considering that LO4 is related to the concept of derivative, which is the central one in the course, meaning it has many prerequisites (LO1, LO2, LO3) and is a prerequisite for mastering all LOs that follow (chronologically) (LO5, LO6, LO7). Looking at the ideal LO weight from LD, LO4 also has a considerable weight, although not the highest in the course. This could imply that the ideal LO4 weight should be increased. However, it should be noted that prioritisation of LOs is done based on several criteria, which are not only related to the course itself but also to the role of the course in the entire study program, for students' future profession and students' pre-knowledge, which is reflected in the required workload. Even though it provides valuable insights about the course, this SNA analysis is blind to the conditions outside the course. For example, if we take LO3 and LO6, we can see that their ideal LO weights are higher than that of LO4. However, these LOs also have higher student workloads and more links to the outside context, which are also criteria affecting the weight. In educational practice, SNA could be used to indicate the central concepts and contribute to determining the ideal LO weights.

To conclude, if LD is sound and prepared by experienced educators, it positively impacts the mastery of LOs.

5.2 RQ2: What are the Different Groups of Learners Based on the Demonstrated Mastery of the LOs?

Identifying High Achievers aligns with existing literature that suggests some students consistently perform well across different assessment types, often due to well-developed learning strategies and a strong alignment with instructional approaches [15]. However, the slightly lower mastery observed for summative LO1, LO2, and formative LO6 within this group indicates that even high-achieving students may encounter specific challenges depending on the content or nature of the LOs. Here, we can note that they did not refresh their pre-knowledge on time (LO1 and LO2 were largely covered in previous education) or needed more time to grasp complex integrative LOs. Interestingly, the student workload planned for LO6 was already higher than expected based on the respective weight, indicating that educators knew it was difficult for students. This highlights the need for continuous refinement of assessment tasks to ensure they accurately measure student understanding across all LOs and often bring student attention to complex topics and prerequisites for developing higher cognitive skills [10].

In contrast, the small size of the Struggling Learners group, characterised by low mastery indicated by both formative and summative assessments, underscores that while most students engage effectively with the course content, a subset of learners still require additional resources and support. Research has shown that students who consistently perform poorly may benefit from targeted instructional support, such as differentiated instruction or formative feedback, which can help address learning gaps and improve outcomes [24] or psychological counselling and professional re-orientation.

The emergence of Summative-Driven Learners as the largest group is particularly noteworthy. These students demonstrate higher mastery in summative assessments than formative ones, suggesting they are more motivated or better prepared for high-stakes evaluations. This indicates that they have a strategic approach to learning, characterised by students organising their learning to achieve a high or positive outcome [14]. This finding resonates with research indicating that some students perform better in summative contexts, where the stakes are higher, and the content is more comprehensive [15]. Moreover, it also implies that formative assessment was helpful for students and that the feedback they received supported them in more LO-oriented learning in preparation for the summative assessment.

Conversely, the Summative Underperformers group, which showed similar mastery in formative assessments as the Summative-Driven Learners but a decline in summative performance, highlights a potential disconnection between formative assessment preparation and summative assessment performance. This phenomenon is supported by literature indicating that some students may struggle with the pressure of summative assessments, leading to underperformance despite adequate preparation during formative activities [1]. The particularly high mastery for formative LO5 in this group suggests that certain LOs may be better suited to formative assessment formats and that alternative summative strategies might be necessary to capture a more accurate picture of student mastery. On the other hand, those students may be exhibiting a surface approach to learning [14], characterised by learners focusing on details and memorising individual pieces of information in a way that signals enough comprehension to complete the assignment.

Overall, these findings underscore the complexity of student learning and assessment. They suggest that, while some students may excel uniformly across different assessment types, others exhibit performance patterns that are influenced by the nature of the assessment itself and their approaches to learning. This highlights the importance of employing various assessment methods to accommodate diverse learner needs and ensure a comprehensive evaluation of student mastery. The representation of LO mastery demonstrated through formative and summative assessments provides a more holistic representation of learners than a simple course grade often provided to quantify academic success [1]. Our study provides a more fine-grained representation of the strengths and weaknesses of learners across the different concepts.

5.3 Practical Implications

At a broader level, the study addresses a significant educational challenge: the need for assessment practices that go beyond mere content evaluation to foster meaningful learning and mastery. Traditional assessment practices often fail to provide actionable insights into student progress or reveal fine-grained patterns of academic performance across different groups of students [2].

The LA conducted in this study can have important practical implications regarding quality assurance of courses, as it provides an evidence base that can be used to introduce necessary educational interventions and "close the loop" to enhance students' acquisition of LOs. First, determining how successful students are in acquiring particular LOs can indicate a need for revising LOs and can motivate educators to rethink and adjust their teaching practices. The analyses such as those conducted in this study can provide valuable insights for enhancing course LD, particularly when it comes to ensuring constructive alignment and links between formative and summative assessment. Notably, the SNA results provide additional insight into determining ideal LO weights and central concepts for students to grasp in the course. Furthermore, insights from the presented analyses can inform educators in providing student support, for example, considering the importance of mastering particular LOs as a prerequisite for mastering other LOs, as indicated by their centrality. Analysing student clusters can also present a basis for better-targeted student support, including cluster-related learning recommendations and more student-centered assessment design.

5.4 Limitations and Future Work

Our study has several limitations. It was conducted on a moderately large (and homogenous) sample, but having more students (possibly more diverse) included in the analyses may provide more comprehensive insights, especially when identifying student clusters. Furthermore, the study was conducted in one specific educational context and one particular course. As different educational environments (e.g., cultures, levels of education) and different subject areas may be associated with different learning habits, it would be valuable to conduct the analyses in the broader context. However, although the context is limited, the findings concerning different assessment types (quite typical in HE context) and methods can be extended to other settings. Therefore, we believe this limitation does not significantly affect the study's generalizability. While the study encompassed one academic year, it would be worth conducting longitudinal research to further explore the potential of the presented learning analytics. It is important to recognise the methodological limitations of the study. Converting continuous assessment grades to fit the CDM models may have led to some loss of information. Future studies must incorporate the continuous assessment scores provided by the instructors to determine LO mastery. Additionally, while the binary output from the CDMs used to quantify LO mastery was sufficient for addressing the research questions, future studies should consider investigating the scores of LO mastery on a continuous scale to gain further insight into the strengths and weaknesses of learners. Future research should also explore the underlying factors contributing to patterns of LO mastery demonstrated by the different clusters, such as the role of assessment design, student motivation, students' approaches to learning, and instructional alignment, to better support all learners in achieving their full potential.

6 Conclusion

This study highlights the critical role of assessment design in shaping students' mastery of learning outcomes (LOs) within higher education study programs. It fills the existing research gap by demonstrating how learning analytics (LA) can be used to map assessment items to specific LOs, quantify mastery, and cluster learners based on their performance.

Using LA techniques such as CDM, ENA, and SNA, we have provided empirical insights into how formative and summative assessments influence students' LO mastery. Combining these techniques offers a comprehensive approach to understanding not only how students perform but why they perform in particular ways. We found that some LOs can have a central position in the study program, being strongly linked to other LOs, which should be adequately reflected in assessment and learning design. We also demonstrated the importance of linking both formative and summative assessment to the intended LOs, emphasising the value of prioritising LOs. The clustering of students based on their LO mastery indicated that students differ in terms of their approaches to learning, which calls for clear student guidance and feedback.

In the larger educational landscape, this approach supports the development of more refined, data-driven learning design and instructional strategies. By ensuring constructive alignment between LOs, teaching and learning activities, and assessment, educators can create more effective learning environments that cater to diverse learner needs. This study also emphasises the potential for LA to enhance continuous course improvement, guiding instructors in making informed decisions that can close the loop in quality assurance and improve educational outcomes across various contexts. Future research should continue exploring LA's integration into LD to address evolving educational challenges and enhance student learning experiences.

Acknowledgments

This study has been supported by the *Innovating Learning Design in Higher Education* - iLed project (funded through the European Union Erasmus+ program, 2022-1-HR01-KA220-HED-000085818) and *Trustworthy Learning Analytics and Artificial Intelligence for Sound Learning Design* – TRUELA project (funded by the Croatian Science Foundation, IP-2022-10-2854).

References

[1] Abhinava Barthakur, Shane Dawson, and Vitomir Kovanovic. 2023. Advancing leaner profiles with learning analytics: A scoping review of current trends and challenges. In LAK23: 13th International Learning Analytics and Knowledge Conference, March 13, 2023. ACM, New York, NY, USA, 606–612. https://doi.org/10.1145/3576050.3576083

[2] Abhinava Barthakur, Jelena Jovanovic, Andrew Zamecnik, Vitomir Kovanovic, Gongjun Xu, and Shane Dawson. 2024. Towards Comprehensive Monitoring of Graduate Attribute Development: A Learning Analytics Approach in Higher Education. In Proceedings of the 14th Learning Analytics and Knowledge Conference, March 18, 2024. ACM, New York, NY, USA, 78–89. https://doi.org/10.1145/3636555.3636852

[3] Sue Bennett, Shirley Agostinho, and Lori Lockyer. 2015. Technology tools to support learning design: Implications derived from an investigation of university teachers' design practices. Comput Educ 81, (February 2015), 211–220. https://doi.org/10.1016/j.compedu.2014.10.016

[4] John Biggs. 1996. Enhancing teaching through constructive alignment. High Educ (Dordr) 32, 3 (October 1996), 347–364. https://doi.org/10.1007/BF00138871

[5] Doug Clow. 2012. The learning analytics cycle. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, April 29, 2012. ACM, New York, NY, USA, 134–138. https://doi.org/10.1145/2330601.2330636

[6] Gráinne Conole. 2013. Designing for Learning in an Open World. Springer New York, New York, NY. https://doi.org/10.1007/978-1-4419-8517-0

[7] Blaženka Divjak, Darko Grabar, Barbi Svetec, and Petra Vondra. 2022. Balanced Learning Design Planning. Journal of information and organizational sciences 46, 2 (December 2022), 361–375. https://doi.org/10.31341/jios.46.2.6

[8] Blazenka Divjak, Nikola Kadoic, and Bojan Zugec. 2021. The Use of Decision-Making Methods to Ensure Assessment Validity. In 2021 IEEE Technology & Engineering Management Conference - Europe (TEMSCON-EUR), May 17, 2021. IEEE, 1–6. https://doi.org/10.1109/TEMSCON-EUR52034.2021.9488580

[9] Blaženka Divjak, Barbi Svetec, and Damir Horvat. 2024. How can valid and reliable automatic formative assessment predict the acquisition of learning outcomes? J Comput Assist Learn January (2024), 1–17. https://doi.org/10.1111/jcal.12953

[10] Blaženka Divjak, Barbi Svetec, Damir Horvat, and Nikola Kadoić. 2023. Assessment validity and learning analytics as prerequisites for ensuring student-centred learning design. British Journal of Educational Technology 54, 1 (January 2023), 313–334. https://doi.org/10.1111/bjet.13290

[11] Blaženka Divjak, Barbi Svetec, Bart Rienties, Paul Astles, Catriona Matthews, Alexander Tillmann, Michael Eichhorn, and Julia schmitt. 2024. Prioritizing Learning Outcomes in Different Learning Design Contexts. In Proceedings of the 35th Central European Conference on Information and Intelligent Systems, September 2024. Faculty of Organization and Informatics, University of Zagreb, Varaždin.

[12] Blaženka Divjak, Petra Žugec, and Katarina Pažur Aničić. 2022. E-assessment in mathematics in higher education: a student perspective. Int J Math Educ Sci Technol 55, 8 (September 2022), 2046–2068. https://doi.org/10.1080/0020739X.2022.2117659

[13] Dante D. Dixson and Frank C. Worrell. 2016. Formative and Summative Assessment in the Classroom. Theory Pract 55, 2 (April 2016), 153–159. https://doi.org/10.1080/00405841.2016.1148989

[14] Noel Entwistle. 1988. Motivation and learning strategies. Educational and Child Psychology 5, (January 1988), 5–20.

[15] Noel Entwistle and P Ramsden. 2015. Understanding student learning. Routledge Revivals.

[16] Seyed M. Ismail, D. R. Rahul, Indrajit Patra, and Ehsan Rezvani. 2022. Formative vs. summative assessment: impacts on academic motivation, attitude toward learning, test anxiety, and self-regulation skill. Language Testing in Asia 12, 1 (September 2022), 40. https://doi.org/10.1186/s40468-022-00191-4

[17] Rob Koper and Bill Olivier. 2004. Representing the learning design of units of learning. Educational Technology & Society 7, 3 (2004), 97–111. Retrieved September 21, 2021 from https://www.j-ets.net/collection/published-issues/7_3

[18] Lori Lockyer and Shane Dawson. 2011. Learning designs and learning analytics. In Proceedings of the 1st International Conference on Learning Analytics and Knowledge, February 27, 2011. ACM, New York, NY, USA, 153–156. https://doi.org/10.1145/2090116.2090140

[19] Lori Lockyer, Elizabeth Heathcote, and Shane Dawson. 2013. Informing Pedagogical Action: Aligning Learning Analytics with Learning Design. American Behavioral Scientist 57, 10 (October 2013). https://doi.org/10.1177/0002764213479367

[20] American Educational Research Association, American Psychological Association, National Council on Measurement in Education. 2014. Standards for educational & psychological testing. Retrieved from https://www.aera.net/Publications/Books/Standards-for-Educational-Psychological-Testing-2014-Edition
[21] Mark Newman. 2010. Networks. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199206650.001.0001
[22] Paul Ramsden. 2003. Learning to Teach in Higher Education. Routledge. https://doi.org/10.4324/9780203507711
[23] David Williamson Shaffer and A. R. Ruis. 2017. Epistemic Network Analysis: A Worked Example of Theory-Based Learning Analytics. In Handbook of Learning Analytics. Society for Learning Analytics Research (SoLAR), 175–187. https://doi.org/10.18608/hla17.015
[24] Valerie J. Shute. 2008. Focus on Formative Feedback. Rev Educ Res 78, 1 (March 2008), 153–189. https://doi.org/10.3102/0034654307313795
[25] Andrew R. Thompson and Logan P. O. Lake. 2023. Relationship between learning approach, Bloom's taxonomy, and student performance in an undergraduate Human Anatomy course. Advances in Health Sciences Education 28, 4 (October 2023), 1115–1130. https://doi.org/10.1007/s10459-023-10208-z
[26] C. P. M. van der Vleuten. 1996. The assessment of professional competence: Developments, research and practical implications. Advances in Health Sciences Education 1, 1 (January 1996), 41–67. https://doi.org/10.1007/BF00596229
[27] Cees P M van der Vleuten and Lambert W T Schuwirth. 2005. Assessing professional competence: from methods to programmes. Med Educ 39, 3 (March 2005), 309–317. https://doi.org/10.1111/j.1365-2929.2005.02094.x
[28] Stanley Wasserman and Katherine Faust. 1994. Social Network Analysis. Cambridge University Press. https://doi.org/10.1017/CBO9780511815478