Decoding Learning Design Decisions: A Cluster Analysis of 12,749 Teaching and Learning Activities

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Abstract

Substantial progress has been made in how educators can be supported to implement effective learning design (LD) with learning analytics (LA). However, how educators make micro-decisions about designing individual teaching and learning activities (TLAs) and how these are related to wider pedagogical approaches has received limited empirical support. This study explored how 165 educators designed and integrated 12,749 TLA in 218 LDs using clustering, pattern-mining, and correlational analysis. The findings suggest most educators use a combination of four common LD TLAs (i.e., Collaboration, Generating independent learning, Assessment, and Traditional classroom activities). The four common TLAs could be used to develop LA and Generative Artificial Intelligence (GenAI) approaches to support educators in making more informed and evidence-based design decisions for effective learning and teaching.

CCS Concepts

• **Applied computing** → **Computer-managed instruction**; **Interactive learning environments**; **Learning management systems**.

Keywords

Learning Design, Learning Analytics, Cluster Analysis, Teaching and Learning Activities, Artificial Intelligence

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1 Introduction

In the last 20 years, substantial progress has been made in how educators can be supported to implement effective learning design (LD) [15, 27]. A range of models and pedagogically informed approaches have been suggested how to best support educators to make effective LD decisions, including the ABC model [12], the AL4LD [10], CHAT [16], FoLA [26], GoLab [25], and OULDI [5]. Furthermore, a range of contributions to new pedagogical practices has provided insights into why LD is pivotal for both effective learning analytics (LA) applications as well as actionable feedback to educators and learners (e.g., [6, 16, 19, 22, 24]).

In a recent work on LD and LA, Macfadyen et al. [14, p. 7] indicated that, while substantial progress has been made in the conceptual development of LD, more research was needed on actual "educator design practices, particularly as they engage with learning analytics and other kinds of teaching and learning evidence. Understanding how educators make design decisions will help us develop better ways to support them in their design work, create an integrated environment of learning and teaching design, delivery and analytic systems, and foster institutional design climates."

In a follow-up review of 49 papers linking LD and LA, Drugova et al. [9, p. 11] indicated that "the research area discussing LA-driven LD improvements still has a way to go before attaining the level of full maturity." Most studies identified by Drugova et al. [9] focus on case studies or implementations of LD within one institution, thereby limiting our understanding and generalization of findings on how educators made LD decisions across different educational contexts.

Therefore, in this study, we aimed to understand how 165 educators have designed 218 LDs in an innovative and free-to-use LD tool called Balanced Design Planning (BDP). The BDP tool has been developed by a range of European universities led by the University of Zagreb [7, 8] partially financed by several EU-funded projects. The BDP tool is based on a combination of two commonly used LD approaches, the ABC model by Laurillard et al. [12] and OULDI [5]. In the BDP tool educators created a wide range of LDs for their respective face-to-face, blended, hybrid, and online courses, and this is the first study that has investigated how these 165 educators designed their LD practices with the support of LA data. Our objective is to uncover potential commonalities in LD practices across educators, with a broader goal of enhancing our understanding of effective learning design. This study advances our theoretical insights into how educators design their learning practice, and how effective LD could be encouraged.

2 Theoretical Background

2.1 Learning Design and Learning Analytics

In this study, LD refers to "the pedagogic process used in teaching or learning that leads to the creation and sequencing of learning activities, the configuration of the environment in which it occurs,

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and the activities performed by the stakeholders to achieve the learning objective that leads to the learning outcome" [1, p. 3]. While related, LD and 'course' are distinct. A course refers to the structured content and activities delivered to students, whereas LD is the pedagogical plan guiding how these elements are organized. This article uses both terms to highlight the relationship between design and implementation.

Recent systematic reviews on LD [1, 9, 15, 27] highlight the need for educators to develop skills in designing and implementing those LD activities to enable rich and deep learning. Several studies suggest that LA applications can support educators in making evidence-based LD decisions [7, 10]. However, as Ahmad et al. [1] note, few of the 161 studies from their LD & LA systematic review used LA dashboards to inform LD practice. Although a systematic literature review on LD and LA is beyond the scope of this study, we will briefly summarize key studies that have applied LD at scale to illustrate the current state of the art.

One of the first studies to link educators' decisions using the OULDI approach with how students were interacting with these LDs on a large scale was at The Open University. For example, Rienties et al. [23] linked the LD decisions of 87 courses with student behavior and performance and found four common clusters of LD practice (i.e., constructivist, assessment-driven, balanced variety, social-constructivist). In follow-up research by Nguyen et al. [19] amongst 38 courses with 43,099 students at The Open University it was shown that 60% of variability in online activities by learners could be linked to how educators made LD decisions, and when students were expected to engage with these activities [18]. Subsequent work by Holmes et al. [11] amongst 47,784 students and 55 courses at again The Open University showed six common clusters of LD practice using a combination of cluster analysis with SNA. Educators' LD decisions mainly differed in how they mixed productive (i.e., creating, doing, making) and communicative (i.e., communicating, debating, sharing) activities weekly.

In a Futurelearn context of 10 MOOCs followed by 49582 learners, Rizvi et al. [24] found that LD decisions made by UK educators influenced learners learning behavior, which inhibited engagement for some groups of cultural learners but encouraged engagement for others. Rizvi et al. [24] identified four common LD activities in these 10 MOOCs, articles, discussions, videos, and quizzes. The frequency and sequence of these common LD activities influenced how worldwide learners engaged in these courses. Misiejuk et al. [17] analyzed the impact of COVID-19 on LD decisions made on 102 courses at The University of Bergen. They found that, during the pandemic, educators substantially changed their LD to include more interactive elements, such as discussion forums and other engagement strategies, while after the pandemic some educators went back to more lecture-based LD. Similarly, in Hong Kong, a multilevel framework of LA-integrated LD patterns by Law and Liang [13] showed how 60 LDs of STEM curriculum units were linked in a 7-step LD triangle of learning outcomes (LO), disciplinary practice, and pedagogical approach. In an inquiry learning spaces tool called Go-Lab more than 16.000 primary and secondary school teachers created and orchestrated learning activities [25], whereby one of the key lessons learned was a need for teachers to have support in designing and orchestrating solutions relevant to their specific context.

These studies indicate that since the first LA-LD empirical papers in 2015, substantial growth and development have occurred in LA-LD research. However, perhaps with the notable exception of Rodríguez-Triana et al. [25], most of these empirical studies were primarily nested in one institutional context, thereby potentially limiting the generalization of the application of LD beyond the boundaries of one context.

2.2 BDP Tool: linking teaching and learning activities with learning outcomes and learning analytics

To the best of our knowledge, one of the few LD databases that are free to use and have been implemented in various institutions is the BDP concept and tool (https://learning-design.eu). The BDP tool has been developed through an iterative process, utilizing the design science methodology, and incorporating insights from OULDI and contemporary research [7, 21]. The initial phases of this work encompassed a needs analysis, a literature review, and an exploration of the existing LD concepts and tools. To ensure its effectiveness and relevance, the validation activities were conducted primarily by higher education educators within Erasmus+ projects (i.e., projects eDesk, Teach4EDU, RAPIDE, and iLED). The BDP tool has a core user base of 1800 individuals from 40 countries worldwide. These educators represent diverse backgrounds, including schools, higher education institutions, lifelong learning providers, and industry professionals. The widespread adoption of the BDP tool underscores its versatility and applicability across various educational contexts and sectors.

Overall, each course's LD in the BDP tool has four parts: Course Details, Planning, LA Analysis, and Export. While various LD tools like GoLab and OULDI provide similar functionality, a unique feature of the BDP tool is the analytical link between the proposed LO, TLA, and LA visualizations of these initial LD decisions in the Analysis phase. A range of dashboard widgets are provided to educators illustrating the learner workload, how the workload is divided amongst six learning types (i.e., acquisition, discussion, investigation, practice, production, assessment) across a course as well as its sub-components, the mode of delivery (on-site, online, hybrid; synchronous, asynchronous; teacher present vs not present; collaboration vs no collaboration; feedback; group activities; types of assessment), and how the LO are related to the assessment and learning units. This helps educators to ensure constructive alignment across the LO, TLA, and learning types [3, 8, 21].

Educators can create TLAs and link them to a particular learning type and LO, as illustrated in Figure 1. The options available for TLAs change based on the selected learning type, activity delivery method, and other factors. In the analysis tab, educators can visualize how their TLA choices have influenced the LD for a particular week and the overall course. A unique feature of the BDP tool is that it automatically generates visualizations using LA to reflect the educators' LD decisions. Another advantage of the BDP tool is its collaborative web-based platform, allowing educators and learners to share designs. Preliminary research shows that sharing these LD and LA data with learners is beneficial for their learning processes [8].

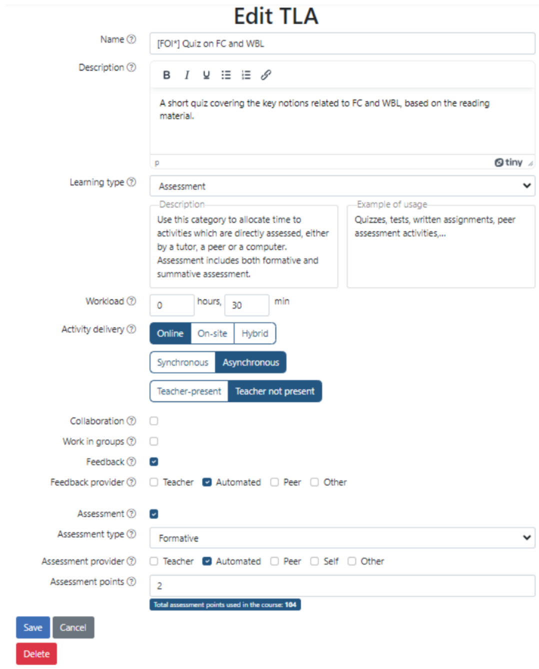

Figure 1: Example of Teaching and Learning Activity in the BDP tool

2.3 Research Questions

While previous studies explore how educators design at broader levels (e.g., learning units or courses), to the best of our knowledge, limited research examines common patterns in micro-level TLA design. Each TLA involves decisions linking it to learning units, pedagogical aims, or outcomes [1, 8, 27], influenced by factors like discipline, student type, and format. We believe common patterns may still emerge across contexts. Identifying these patterns from large datasets could enhance LD and LA research, enabling Artificial Intelligence to recommend optimal TLA combinations. Using data from 218 courses by 165 educators, we aim to find common LD patterns among 12,749 TLAs: **RQ1: What are the common patterns or clusters that educators typically use to design and implement teaching and learning activities (TLA), and what patterns can be identified within these clusters?**

Specifically, RQ1 explores patterns or clusters in terms of the types of activities (e.g., discussions, assessments, collaborative tasks) and the modes of delivery (i.e., face-to-face, online, blended) employed. We seek to identify these patterns at the granularity of individual courses, aiming to understand if there are commonalities across courses. In addition, we aim to explore potential relationships between TLAs and learning outcomes: **RQ2: Which aspects of TLA and learning outcomes (LO) are correlated at the course level?**

By examining these correlations, we seek to understand how the structure and type of TLAs influence the overarching goals of a course (i.e., the LOs). Identifying potential relationships between specific TLAs and LOs could provide insights into the effectiveness of various teaching strategies from a design perspective. For example, this knowledge could inform future LDs and educator practices by highlighting which activities are aligned with achieving desired learning outcomes, thereby contributing to LD theory and practice.

3 Methodology

3.1 The BDP Tool Database

The BDP tool was launched for participating project institutions in September 2021 and made publicly available in December 2021. The dataset comprises 13,466 TLAs from 218 courses, uploaded by educators from various, mainly European, countries. For this analysis, we used data from 2022-2023 for which designers gave consent. Data were extracted and transformed using Python, specifically leveraging the Pandas and NumPy libraries for data manipulation. This dataset is structured at the TLA level, with each row representing a unique TLA within a course. This granular level allowed us to analyze LD patterns across courses. For instance, the following TLA features were extracted:

- learning_type: Includes six learning types –'lt_acquisition', 'lt_discussion', 'lt_investigation', 'lt_practice', 'lt_production', 'lt_assessment'—capturing various pedagogical approaches.
- tla_mode_of_delivery: Describes the mode of delivery for the activity, with levels 'Online', 'Onsite', or 'Hybrid'.
- tla_synchronous: Categorizes activities as either 'is-sync' (synchronous) or 'not-sync' (not synchronous).
- tla_collaboration: Indicates if an activity involves collaboration, with levels 'has-collab' (involves collaboration) or 'no-collab' (does not involve collaboration).
- tla_teacher_present: Captures the presence of a teacher in the activity, with options 'has-teacher' (teacher is present) or 'no-teacher' (teacher is not present).

- tla_assessment: Identifies if the TLA involves assessment, with levels 'is-assessment' or 'not-assessment'. This option is typically selected when the learning type is also "assessment". However, as shown in Figure 1, any of the other five (non-assessment) learning types can also have this option selected, which usually means that the TLA involves formative assessment.
- tla_has_groups: Depicts whether the activity involves student groups, categorized as 'has-groups' (involves groups) or 'no-groups' (does not involve groups).
- tla_feedback: Indicates whether feedback is involved in the activity, with options 'is-feedback' (involves feedback) or 'not-feedback' (does not involve feedback).

For the correlation analysis, this dataset was aggregated at a course level. This process condensed the features above into a broader course overview based on the count of each TLA type and its attributes. This approach allowed us to examine potential correlations between TLA features and learning outcomes at a course level.

3.2 Measurement and analysis

A series of pre-processing steps were undertaken to clean and refine the dataset, laying a strong foundation for precise data analysis. While key steps are outlined below, the source code with full details is available at https://github.com/josmarios/ld-clustering.

To address missing values in the TLA's mode of delivery, we initially filled them with the mode of delivery from the corresponding LD. The BDP tool offers flexibility in TLA design, allowing some fields, like the mode of delivery, to be left unspecified, which led to missing data points. We resolved this by using the overall course's mode of delivery to fill these gaps. The dataset was then refined based on quality criteria, excluding LDs with fewer than 10 TLAs or those labeled as 'test,' as these might indicate incomplete or experimental designs. This filtering reduced the dataset from 444 to 218 LDs, with a total of 12,749 TLAs, ensuring a more reliable basis for analysis.

The data analysis consisted of two distinct phases, one per research question. While the first phase involved clustering analysis conducted at a TLA level (n = 12,749), the second phase focused on correlation analysis at a course level (n = 218). Accordingly, the data in the second phase underwent a comprehensive data aggregation process in which TLA attributes were summed up to the course level (see Section 3.1).

3.2.1 Phase 1: Clustering Analysis. In this phase, we identified natural groupings, or "clusters," within TLAs based on their characteristics. This was accomplished using the "k-modes clustering" approach for categorical data [4]. Accordingly, the clustering analysis centered on the categorical variables presented in Section 3.1 (tla_synchronous, tla_collaboration, tla_teacher_present, tla_assessment, tla_has_groups, tla_feedback, tla_mode_of_delivery, and learning_type), capturing various facets of TLAs.

In line with standard approaches for clustering analysis [20], we used the KModes library in Python, taking the following steps:

Optimal Number of Clusters: To decide how many clusters to form, we applied the "elbow method." This involves running the k-modes algorithm several times with different numbers of clusters (k) until finding a 'k' that yields the best fitting of the data (the "elbow point").

Hyperparameter Fine-Tuning: Hyperparameter values were selected using a random search strategy, varying the initialization methods ('Huang', 'Cao', 'random'), the number of initial conditions ('n_init'), and the maximum number of iterations ('max_iter').

Final Clustering: Once the best k and hyperparameter values were identified, we applied k-modes clustering to assign each TLA to the most suitable cluster, based on the TLA characteristics.

Cluster Profiling: Post-clustering, each cluster was profiled using bar plots and statistical metrics such as mode, frequency, and percentages. These profiles allowed us to interpret the common characteristics within clusters.

Pattern Mining within Clusters: Frequent patterns were identified using the FP-Growth algorithm. This method was used to understand underlying associations between variables that were not immediately apparent, revealing frequent combinations of TLAs (e.g., common sets of co-occurring TLAs within each cluster).

Elbow plots were used to determine the optimal number of clusters, thereby supporting the robustness of the clustering approach. Additionally, bar plots were employed to profile the characteristics of each cluster, aiding in the interpretability of our findings. We also provided a heatmap for better insights into the potential correlations.

3.2.2 Phase 2: Correlation Analysis. This phase focused on RQ2, where correlation tests were conducted to understand potential relationships between specific TLAs and LOs. Accordingly, the following steps were taken:

1. **Data Aggregation and Pre-processing**: The original dataset contained individual TLAs. We aggregated these by course, resulting in columns that represent the count of each TLA aspect for each course:
   - TLA Aspects: These columns contain information on various TLAs. This includes whether the activity is synchronous ('tla_synchronous'), collaborative ('tla_collaboration'), has a teacher present ('tla_teacher_ present'), serves as an assessment ('tla_assessment'), involves group work ('tla_has_groups'), or feedback ('tla_feedback').
   - Mode of Delivery: These columns describe the format in which the course content is delivered. The options are online ('tla_online'), onsite ('tla_onsite'), or a hybrid of both ('tla_hybrid').
   - Learning Outcomes: These columns capture the different types of LO targeted by the course. Variables include levels of Bloom's taxonomy of cognitive skills from remembering ('tla_lo_remembering') to creating ('tla_lo_creating'), encompassing understanding ('tla_lo_understanding'), applying ('tla_lo_applying'), analyzing ('tla_lo_analysing'), and evaluating ('tla_lo_evaluating').
2. **Outliers Handling**: Courses with outliers in two or more columns were excluded from the dataset (i.e., values exceeding three standard deviations from the mean). The remaining outliers were winsorized to limit extreme values.
3. **Correlation Testing**: Pearson's correlation coefficients were calculated and the correlation matrix was visually presented using a heatmap.

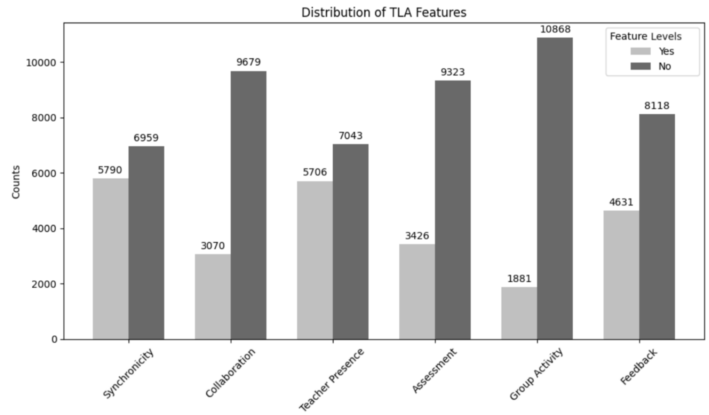

Figure 2: Distribution of TLA features within the dataset. 'Yes' indicates the presence and 'No' indicates the absence of features (e.g., synchronicity, feedback, etc.)

(4) **Significance and Confidence Intervals**: Confidence intervals were also computed to understand the reliability of each correlation. Only correlations that were both statistically significant and had effect sizes greater than a predetermined threshold were further interpreted.

4 Results

This section addresses our research questions by firstly examining the distribution of TLAs within the dataset, and then presenting findings from our cluster and correlation analyses. Figure 2 shows the TLA distribution, indicating varying degrees of strategy implementation by educators. Notably, activities involving teacher presence (i.e., a teacher being present in a TLA, 5,706 instances) and synchronous interaction (5,790 instances) are more common, suggesting a preference for direct and real-time engagement in educational settings. In contrast, activities focusing on collaboration (3,070 instances), group work (1,881 instances), assessment (3,426 instances), and feedback (4,631 instances) are less frequent, pointing to potential areas for pedagogical development.

Table 1 provides insights into TLAs' mode of delivery and learning type, revealing a predominant use of online delivery (66.1% of TLAs), with significant engagement in knowledge acquisition (21.6%) and assessment activities (11.0%) through this mode. Hybrid and onsite modes account for 15.2% and 18.7% of TLAs, respectively, with practice activities (5.9% onsite) highlighting fewer direct interactions or physical resources in certain learning types. The data illustrates an overview of educational delivery methods and their alignment with different types of learning.

4.1 Phase 1: Clustering Analysis of learning design

As mentioned in Section 3.2, we used the elbow method to determine the optimal number of clusters. Figure 3 shows that the cost function – a representation of within-cluster variance – starts to level off at k = 4, suggesting that adding more clusters beyond this number does not substantially enhance the compactness of the data grouping. Therefore, Phase 1 was based on four clusters.

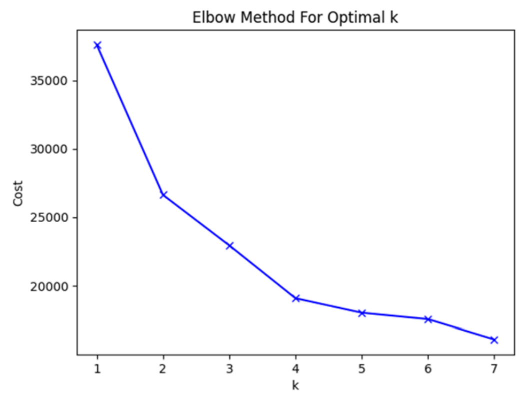

Figure 3: Results of the Elbow method suggest a potential optimum k = 4

Subsequently, we applied k-modes to categorize the TLAs. The characteristics of each cluster are visually represented in bar plots, which offer a quick and comprehensive understanding of the predominant aspects of TLAs in each cluster (see Figure 4). For example, the first row in Figure 4 illustrates how many TLA activities were classified by educators as synchronous activities across clusters (columns T, C, A, and G). Most activities in clusters T and C (see Sections 4.1.1 and 4.1.2) were synchronous, while relatively few activities were synchronous in clusters A and G (see Sections 4.1.3 and 4.1.4).

In terms of collaboration activities, cluster C had most of these activities, while for example whether or not a teacher was present during a TLA was most common in cluster T, and least common in cluster G. The detailed descriptions of the four clusters are provided below. To supplement the bar plots and provide a more granular view, we tabulated the most frequent categories (mode), their frequencies, and their percentages for each cluster (see Table 2). In addition, Table 3 provides the top rules (i.e., the ones with the highest confidence) produced by the FP-Growth algorithm for each cluster. Based on these findings the authors labeled the four cluster

Table 1: Cross tabulations between mode of delivery and learning type.

Mode of Delivery	Learning Type						Total
	Acquisition	Assessment	Discussion	Investigation	Practice	Production	
Hybrid	591 (4.6%)	208 (1.6%)	518 (4.1%)	135 (1.1%)	318 (2.5%)	164 (1.3%)	1934 (15.2%)
Online	2750 (21.6%)	1398 (11.0%)	1454 (11.4%)	1042 (8.2%)	1068 (8.4%)	713 (5.6%)	8425 (66.1%)
Onsite	629 (4.9%)	198 (1.6%)	467 (3.7%)	167 (1.3%)	748 (5.9%)	181 (1.4%)	2390 (18.7%)
Total	3970 (31.1%)	1804 (14.2%)	2439 (19.1%)	1344 (10.5%)	2134 (16.7%)	1058 (8.3%)	12749 (100.0%)

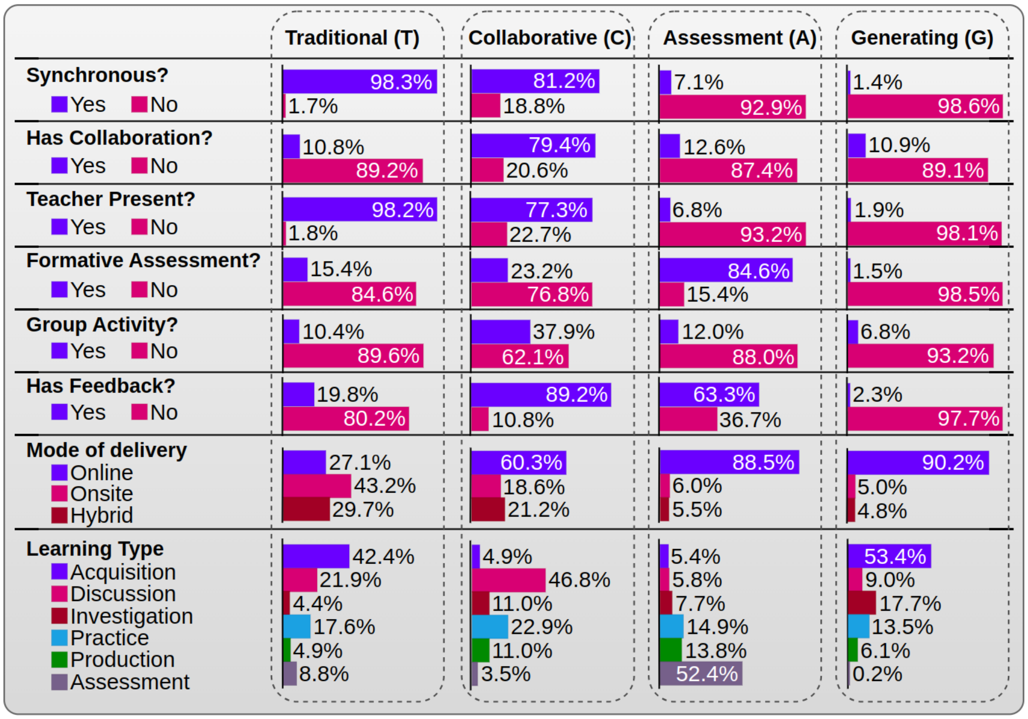

Figure 4: Distribution of TLA aspects (rows) per cluster (columns).

results based upon the presented data categorizations and classifications in other LD taxonomies like the ABC model and the OULDI model. These are explained next.

4.1.1 Generation of knowledge/skills/competences through independent learning (G). Regarding the cluster profiles, the most common LD TLA in the BDP tool (30.61%) was the generation of knowledge, skills, and competencies through independent learning (G). This TLA was primarily asynchronous without a teacher being present, focused on the individual learner, primarily online. The pedagogical focus of G was on the acquisition of knowledge, skills, and competencies. It is perhaps surprising that this was the most commonly used LD TLA given that many educators in the BDP tool were from teaching at non-distance face-to-face teaching and learning institutions.

- **Activity Type**: Asynchronous ('not-sync') and without a teacher ('no-teacher'), similar to Assessment (A) but stands out for not being assessment-focused ('not-assessment' at 98%).
- **Structure**: Highly individual-focused ('no-collab' at 89%, 'no-groups' at 93%), suggesting an emphasis on independent work.
- **Mode of Delivery**: Almost exclusively online (90%), the highest among all clusters.
- **Learning Type**: Predominantly 'lt_acquisition' (53%), but without assessments, making it unique in its focus on individual learning acquisition.
- **FP-Growth Insights**: There was almost certain confidence (around 99.8%) that in online learning settings focused on individual acquisition ('lt_acquisition') with no teacher ('no-teacher') or collaboration ('no-collab'), group activities are almost invariably absent ('no-groups').

4.1.2 Traditional classroom activity (T). The second most common LD TLA (29.57%) was what we labeled as the traditional classroom activity (T). This TLA was primarily synchronous in the classroom with a teacher present and teacher-led, and would typically form part of a lecture, seminar, teaching session, or lab session. Like G

Table 2: Profile of each cluster providing the mode, frequency of mode, and percentage for each cluster.

Cluster	Size	Statistic	Synchronous?	Collaboration?	Teacher Present?	Assessment?	Has Groups?	Has Feedback?	Delivery	Learning Type
		Mode	No	No	No	No	No	No	Online	Acquisition
G	3903	Freq	3980	3597	3961	3976	3764	3945	3642	2157
		%	98.56	89.08	98.09	98.46	93.21	97.70	90.19	53.42
		Mode	Yes	No	Yes	No	No	No	Onsite	Acquisition
T	3770	Freq	3604	3270	3601	3103	3285	2940	1584	1555
		%	98.28	89.17	98.20	84.62	89.58	80.17	43.20	42.41
		Mode	No	No	No	Yes	No	Yes	Online	Assessment
A	3105	Freq	2466	2319	2473	2246	2335	1680	2348	1391
		%	92.92	87.38	93.18	84.63	87.98	63.30	88.47	52.41
		Mode	Yes	Yes	Yes	No	No	Yes	Online	Discussion
C	1971	Freq	1940	1897	1847	1836	1484	2131	1440	1119
		%	81.17	79.37	77.28	76.82	62.09	89.16	60.25	46.82

Table 3: Rules generated by FP-Growth with the highest confidence for each cluster

Cluster	Rule	Target	Confidence
G	('Online', 'lt_acquisition', 'no-collab', 'not-sync')	('no-groups',)	0.998438
G	('Online', 'lt_acquisition', 'no-collab', 'no-teacher', 'not-sync')	('no-groups',)	0.998419
G	('Online', 'lt_acquisition', 'no-collab', 'not-feedback', 'not-sync')	('no-groups',)	0.998393
T	('lt_acquisition', 'no-groups')	('has-teacher',)	0.996745
T	('is-sync', 'lt_acquisition', 'no-groups')	('has-teacher',)	0.996704
T	('lt_acquisition', 'no-groups', 'not-assessment')	('has-teacher',)	0.996624
A	('Online', 'lt_assessment', 'no-collab', 'no-teacher', 'not-sync')	('no-groups',)	0.991620
A	('lt_assessment', 'no-collab', 'no-teacher', 'not-sync')	('no-groups',)	0.990983
A	('is-assessment', 'lt_assessment', 'no-collab', 'no-teacher')	('no-groups',)	0.990950
C	('is-feedback', 'is-sync', 'no-groups')	('has-teacher',)	0.972468
C	('has-collab', 'has-teacher', 'is-feedback')	('is-sync',)	0.963824
C	('has-teacher', 'is-feedback')	('is-sync',)	0.942225

also in this activity T the pedagogical focus was on the acquisition of knowledge, skills, and competencies, but the main differences seemed to be teacher presence and the focus on synchronous, mostly face-to-face activities.

- **Activity Type**: Predominantly synchronous ('is-sync' at 98%) with a teacher present ('has-teacher').
- **Structure**: Highly individual-focused ('no-collab' at 89%, 'no-groups' at 89%), suggesting a lack of collaborative activities.
- **Mode of Delivery**: Mostly onsite (43%), which was unique among the clusters.
- **Learning Type**: Strong focus on 'lt_acquisition' (42%), emphasizing the traditional method of information transfer.
- **FP-Growth Insights**: The algorithm exhibited extremely high confidence (nearly 99.7%) that in settings focused on individual acquisition of information ('lt_acquisition') and where group activities were absent ('no-groups'), a teacher was almost certainly present ('has-teacher').

4.1.3 Assessment activity (A). The third most commonly used LD TLA (24.35%) used in the BDP tool was assessment activity (A). This TLA was primarily asynchronous without a teacher being present, focused on the individual learner, and the pedagogical focus was on the assessment of knowledge, skills, and competencies, and providing/receiving feedback.

- **Activity Type**: Distinguished by its asynchronicity ('not-sync' at 93%) and absence of a teacher ('no-teacher' at 93%).
- **Structure**: Individual-focused ('no-collab', 'no-groups'), but uniquely characterized by a high focus on assessments ('is-assessment' at 85%).
- **Mode of Delivery**: Overwhelmingly online (88%).
- **Learning Type**: Leans towards 'lt_assessment' (52%), suggesting it had assessment-oriented courses.
- **FP-Growth Insights**: The algorithm showed near certainty (around 99.1%) that in online environments focused on assessment ('lt_assessment'), where neither collaboration ('no-collab') nor a teacher ('no-teacher') was involved, there were likely no group activities ('no-groups')

4.1.4 Collaborative classroom activity (C). The least commonly used LD (15.46%) used in the BDP tool was the collaborative classroom activity (C). This TLA was primarily synchronous in various online, blended, and face-to-face formats with a teacher present. However, in contrast to the other three, this was highly collaborative, where the pedagogical focus was on discussions, skills, and competencies, and providing/receiving feedback.

- **Activity Type**: Synchronous ('is-sync'), but uniquely characterized by its strong emphasis on teacher presence ('has-teacher') and feedback ('is-feedback' at 89%).

- **Structure**: Highly collaborative ('has-collab' at 79%), which sets it apart from other clusters.
- **Mode of Delivery**: Primarily online (60%), notable for its blend of online and collaborative elements.
- **Learning Type**: A particular focus on 'lt_discussion' (46.8%), highlighting dialogic forms of learning.
- **FP-Growth Insights**: There was high confidence (about 97%) that when the environment was synchronous ('is-sync') and had no group activities ('no-groups'), it was highly likely that a teacher would be present ('has-teacher'). Furthermore, there is also strong confidence (around 96%) that in settings where a teacher is present and feedback is given ('is-feedback'), the activity is likely to be synchronous ('is-sync').

4.2 Phase 2: Correlation Analysis

In this phase, we present the results of our correlation analysis, which examined relationships between various aspects of TLAs across 218 courses. We used both visual and quantitative methods to analyze the data. Accordingly, Figure 5 shows the overall interrelationships between variables, and Table 4 lists TLAs with statistically significant correlations with larger Pearson correlation coefficients (r > 0.6).

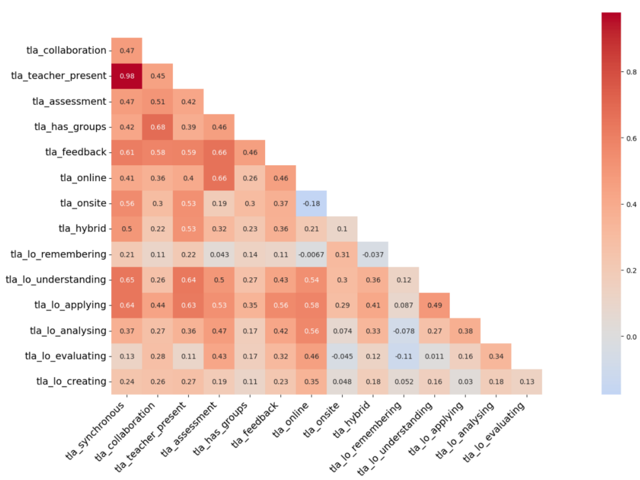

Figure 5: Heatmap indicating the correlations between each pair of variables.

These results can be summarized as follows:

- **tla_synchronous and tla_teacher_present:** A remarkably strong positive correlation of $r = 0.98$ existed between synchronous teaching and the presence of a teacher. This finding suggests that teacher-led settings were overwhelmingly synchronous.
- **tla_synchronous with various variables:**
  - **tla_feedback:** A moderate positive correlation ($r = 0.61$) implied that feedback mechanisms were often incorporated into synchronous teaching.
  - **tla_lo_understanding and tla_lo_applying:** These LOs shared moderate correlations with synchronous settings ($r = 0.65$ and $r = 0.64$, respectively), suggesting a focus on understanding and applying concepts.
- **tla_collaboration and tla_has_groups:** A correlation of $r = 0.68$ indicated that collaborative learning commonly involved group activities.
- **tla_teacher_present with various variables:**
  - **tla_lo_understanding and tla_lo_applying:** These variables showed moderate correlations ($r = 0.64$ and $r = 0.63$, respectively) with the presence of a teacher, pointing to the teacher's role in achieving specific LO.
- **tla_assessment with various variables:**
  - **tla_feedback:** A correlation of $r = 0.66$ suggested that assessment methods often incorporated feedback mechanisms.
  - **tla_online:** A similar correlation ($r = 0.66$) implied that assessments were increasingly aligned with online teaching resources.
- **Level of LOs with various variables:**
  - LOs with lower levels (understanding and applying) are correlated more than higher-level LOs with synchronous TLAs and teacher presence.

5 Discussion

In this LA and LD study, we explored common TLAs utilized by 165 educators in planning 218 LDs through the BDP tool, a research-based solution for learner-centered LD. First, we identified common LDs among 12,749 TLAs using a clustering analysis, which showed that the most common learning type identified was the acquisition, followed by discussion, practice, and assessment (see Table 1). The acquisition was more common in online courses, and a balance between synchronicity and teacher presence was also evidenced within our dataset (see Figure 2). However, collaboration and feedback were often not incorporated in most TLAs. Second, we explored correlations between TLAs and LOs at a course level, which showed that feedback was most closely related to synchronous activities. Our implicit and explicit assumptions in this study were that if we can identify and distill common TLAs among a vast range of educators nested within different disciplines and settings, we as learning scientists might help with developing, implementing, and evaluating subsequent automatic recommendations using AI [1, 9, 24]. For example, Gen-AI could use these results to suggest which combinations of TLAs might be useful for a particular learning situation, or help to identify specific TLAs for certain levels of LOs or specific learners.

The clustering analysis revealed four distinct clusters representing different LD TLAs, each characterized by unique patterns in terms of the features we presented in Section 2.2 (tla_synchronous, tla_collaboration, tla_teacher_present, tla_assessment, tla_feedback, tla_has_groups, tla_mode_of_delivery, and learning_type). These LD TLAs included four clusters: Collaborative activities (C), Assessment activities (A), Traditional Classroom activities (T), and Generation of knowledge/skills/competencies through independent learning (G). Furthermore, the correlation analysis highlighted relationships between different TLA aspects, offering an understanding of how these elements often co-occur and influence each other in the LD process.

Table 4: Aspects of TLAs with statistically significant correlations and r >0.6.

Variable 1	Variable 2	Correlation (r)	p-value	CI (lower)	CI (upper)	Effect size (R^2)
tla_synchronous	tla_teacher_present	0.978	<0.001	0.971	0.983	0.956
tla_synchronous	tla_feedback	0.610	<0.001	0.519	0.687	0.372
tla_synchronous	tla_lo_understanding	0.646	<0.001	0.562	0.718	0.418
tla_synchronous	tla_lo_applying	0.642	<0.001	0.557	0.714	0.412
tla_collaboration	tla_has_groups	0.683	<0.001	0.605	0.748	0.466
tla_teacher_present	tla_lo_understanding	0.636	<0.001	0.550	0.709	0.405
tla_teacher_present	tla_lo_applying	0.630	<0.001	0.542	0.704	0.397
tla_assessment	tla_feedback	0.661	<0.001	0.579	0.730	0.437
tla_assessment	tla_online	0.662	<0.001	0.580	0.731	0.438

One key finding was the alignment and divergence of the learning types identified in each cluster with established models such as the ABC model and OULDI [5, 12]. While these two approaches, as well as the concept and the BDP tool, use six and seven distinct learning activity types, our analyses suggest that most educators in the BDP tool used four learning types more often (i.e., acquisition, discussion, practice, assessment) and less used production and investigation (see Table 1). Additionally, the clustering of TLAs into distinct LDs reflected certain aspects of these models, suggesting a separate interaction of synchronous and asynchronous activities, the presence or absence of a teacher, and the focus on individual or collaborative learning. In addition, the focus on acquisition in both T and G clusters reflects the core emphasis on knowledge and skill development found in the ABC model and OULDI frameworks.

To some extent it was unexpected to observe that only a third of the 12,749 TLA activities incorporated formative assessment and collaboration, especially considering the emphasis in existing literature on the pivotal role of these activities in learners' better acquisition learning outcomes [2, 9, 12, 15, 17, 18, 22]. Several studies found that assessment drives student learning, and in online contexts, collaboration activities fundamentally determine student engagement and subsequent study performance [19, 22]. This observation prompts a reflection on educators' strategies and the potential untapped opportunities for integrating these elements more extensively in LDs.

Furthermore, the delineation of distinct TLA offers a structured lens to approach LD, aiding educators in crafting learning experiences that are both rich and varied. In particular, the insights derived from the clustering analysis could guide educators to balance different elements such as collaboration, feedback, and assessment in their LDs, creating spaces for diverse learning needs and preferences. For example, the high prevalence of independent LD TLA suggests a shifting paradigm towards learner autonomy, urging educators to facilitate environments that focus on independent and self-directed learning. This suggests a reflective approach to LD, encouraging educators to use the core insights regarding the distinct TLA to make adaptable and responsive learning spaces.

Another key finding was the resonance and divergence of the current study's results when compared with previous cluster analyses in LD research (e.g., [11, 18, 19, 22, 23]). The identification of distinct TLA in the present study echoes the findings of earlier research that delineated common clusters of LD practice, such as constructivist, assessment-driven, and social-constructivist approaches. However, the current study advances this discourse by exploring the micro-level LD TLA, exposing the distinct dynamics behind the design of individual TLAs. This granular approach to clustering not only supports the complex nature of LD practices highlighted in previous studies but also shows TLAs that can potentially serve as foundational elements in the LD process. In summary, these findings extend existing literature by providing a detailed perspective to better understand LD, and by enhancing our comprehension of the small-scale elements of LDs.

Finally, this study revealed correlations between various TLAs and LOs, providing valuable insights for educators to design courses that align with their intended outcomes. For instance, lower-level LOs (e.g., understanding and applying) were associated with synchronous teaching and teacher presence, reflecting their alignment with traditional educational activities. By correlating specific TLAs with distinct LOs, educators can create more targeted course designs based on empirical evidence. Additionally, these insights could guide the development of AI-based solutions to recommend TLA combinations for different contexts, advancing data-driven, personalized learning. This finding underscores the potential of integrating LA into the LD process, promoting a future of evidence-based and customized education.

5.1 Future Directions

Looking forward, it is imperative to address the gaps in the current research to foster a more comprehensive understanding of LD [2, 9]. While this study offers rich insights into common TLAs in LD, it also highlights the need for further research into the micro-level dynamics of LD. Future studies should aim to explore the distinct relationships of various TLAs, their common and less common sequences, and how these TLAs relate to actual learning processes and intended LOs. This may offer a more detailed understanding of how different TLAs can be combined for effective learning as previous studies conducted in other contexts have shown that LD decisions substantially influence students' learning processes and academic performance [21–23]). Moreover, there is a need to explore the potential biases and limitations inherent in the current dataset, paving the way for more inclusive and representative research in the future.

Furthermore, we stress the possibilities for further integration of LA and LD [1] (e.g., by offering a data-driven approach to crafting effective learning environments). Future research should leverage the synergies between LA and LD to foster a new era of education that is both evidence-based and finely tuned to meet individual learning objectives. This creates opportunities for more tailored learning experiences and paves the way for AI tools that can give specific advice, promoting a learning environment adaptive and responsive to the needs of individual learners.

5.2 Limitations

Despite the insights into LD, this study is not devoid of limitations. The reliance on the BDP tool, which structures the design process in a specific way, may introduce bias. Additionally, the cluster analysis resulted in only four clusters, which may not fully capture the global diversity of LD practices. Furthermore, we have not distinguished between educational levels or formal and informal training. The focus on clustering and correlation analyses also limits the exploration of causal relationships, prioritizing pattern identification over causal inference. Accordingly, this study sets the stage for future research to investigate these dynamics more deeply.

In the context of existing literature, this study navigates a rapidly evolving field with diverse perspectives and theories [1, 15, 24, 27]. While it builds upon and refers to a range of established models and theories, it might not encompass all relevant viewpoints or recent advancements in the field. The dynamic nature of the educational landscape, characterized by the continuous emergence of new tools and approaches, poses a challenge in drawing a comprehensive picture that is fully representative of the current state of LD and LA. Therefore, while the study offers valuable insights, it should be viewed as a contribution to a larger discourse as it might not capture all emerging perspectives in LD.

6 Conclusion

In this study, leveraging a dataset of 12,749 TLAs designed between 2022 and 2023 on the BDP tool, we explored how educators made key LD decisions, such as selecting TLAs and instructional strategies. Our findings revealed that knowledge acquisition remains the most common learning type, especially in online course delivery. The integration of collaboration, formative assessment, and feedback in TLAs remains relatively low. Additionally, teacher presence and feedback are highly correlated with synchronous activities. The clustering analysis revealed four distinct clusters: Collaborative activities, Assessment activities, Traditional Classroom activities, and Generation of knowledge through independent learning. Overall, the results suggest that learning designers still do not make sufficient use of innovative pedagogies and contemporary research insights when preparing learner-centered LDs.

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