

RESEARCH ARTICLE

Open Access



Understanding the role of learning analytics and generative artificial intelligence on decision-making and learning design practice in higher education

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Abstract

High-quality learning design is an important contributor to student success. Higher education institutions can leverage the combined potential of learning analytics (LA) and Generative Artificial Intelligence (GenAI) to enhance instructors' learning design practices. However, the way LA and GenAI are being used in combination for learning design is not well understood. In this context, one theory that can provide valuable insights into instructors' technology integration into learning design (LD) practice is Self-Determination Theory (SDT). Using SDT as an interpretative lens, this study illuminates the factors in instructors' learning design practices when utilising LA and GenAI. For this purpose, we employed quantitative ethnography to explore how instructors utilise LA and GenAI for LD. Eleven focus groups were conducted with instructors from a large Australian university. Using thematic analysis, we created a codebook consisting of ten codes that were applied to our dataset and then analysed using Epistemic Network Analysis (ENA). Our results show that instructors' LA-informed LD discussions primarily revolved around course, contextual, and creative problem-solving considerations, as well as student support. The predominant GenAI factors were assessment design, contextual consideration, creative problem solving and design for student self-determination. Based on our results, we discuss the integration of LA and GenAI in LD practice and decision-making, highlighting the practical implications of our findings.

Keywords Learning design, Decision-making, Epistemic network analysis, Generative artificial intelligence, Learning analytics, Creative problem solving

Introductions

The alignment between learning design (LD) and learning analytics (LA) has the potential to improve LD practice in higher education. LA offers instructors and learning designers insights into learner behaviours and engagement patterns, thereby supporting processes of reflection and sensemaking that can improve student learning experiences (Mangaroska & Giannakos, 2018). Central to this endeavour is the articulation of

pedagogical intent and its comparison with observed learner activity, a dual perspective that enables instructors to evaluate the extent to which design goals are realised (Lockyer et al., 2013). In this framing, LD specifies the pedagogical intent in terms of what learners are expected or anticipated to do and how they are assessed. LA then provides evidence of the student's behaviour and engagement. The alignment between LD and LA is essential for meaningful interpretation of future revisions (Buckingham Shum et al., 2023; Lockyer et al., 2013).

The research literature has demonstrated the importance of framing and reporting on LD as a means to understand and interpret LA data within meaningful LD contexts. For example, the Open University Learning Design Initiative (OULDI) (Rienties & Toetenel, 2016) demonstrated that faculty design decisions significantly influence weekly student engagement patterns (LA). The temporal analyses attributed roughly two-thirds of weekly engagement to implemented course design (Nguyen et al., 2017; Rienties & Toetenel, 2016). In follow-up studies, activities were framed using a taxonomy that highlighted the specific design choices that were associated with student retention and satisfaction outcomes. While LA has the potential to provide strong predictive elements, these are simply snapshots in time that reveal engagement patterns without identifying the underlying reasons for an educator's design decisions. Mixed-method research has shown that LA reveals common behavioural patterns across many courses, yet "why" educators implement a specific course design remains hidden without further qualitative inquiry (Nguyen et al., 2022). We argue in this paper for a process-oriented, theory-led approach to understanding design intentions alongside trace-based outcomes.

There remains a notable gap between the potential and the actual use of LA-informed design across institutions (Alzahrani et al., 2023). Adoption is uneven, and transferring "successful" approaches between contexts requires attention to local social, organisational, and cultural conditions (Dawson et al., 2018; Tsai et al., 2020; Viberg et al., 2018). The practicable LA perspective foregrounds this point: the social artefact, what instructors and students actually do together, determines whether LA will be used; "what is not practicable is not likely to be used" (Viberg & Grönlund, 2023). Human-centred LA (HCLA) therefore emphasises participatory design, usability, and usefulness in real settings, and calls out the design dimension of LA as underdeveloped relative to theory and data science (Buckingham Shum et al., 2019; Dimitriadis et al., 2021).

To date, LA has provided snapshots to support educator reflection. However, instructors increasingly need more process-oriented insights that connect fine-grained activity data with evolving LD intentions. Research to link LD more tightly to LA (e.g., moving beyond "click counts" to time-on-activity and on-track status) has been suggested to make interventions more timely and actionable (Nguyen et al., 2022). GenAI offers additional potential in this space, not as an autonomous solution, but as a scaffold for continuous, nuanced feedback on design and for assistance with specific design tasks (e.g., assessment prompts, exemplar feedback, multimedia development). Early evidence suggests that clusters of teaching and learning activities can be leveraged to build LA-and-GenAI supports that can help educators to make more informed, evidence-based design decisions (Albuquerque et al., 2025). However, there remains a lack of a nuanced understanding of how educators undertake the practice of design when engaging with LA and GenAI. While predictive insights and technical affordances are valuable, they only partially illuminate the lived realities of LD. To fully understand the uptake and impact of

LA and GenAI, research must attend to the motivational and relational dynamics that underpin instructors' LD practices.

Self-determination theory (SDT) provides a valuable framework for understanding instructors' decisions in workplace settings (Deci & Ryan, 1985). This theory posits that human motivation and optimal performance are supported when three innate psychological needs are met: autonomy, competence, and relatedness. When instructors' basic psychological needs are fulfilled in higher education, this can promote collaborative relationships among institutions, faculty, and students, ultimately improving motivation, well-being, engagement, and academic outcomes (Hutomo & Kurniawati, 2024). Conversely, when these needs are thwarted, their motivation and, consequently, performance decline (Ryan et al., 2021). Examining instructors' discourse about LA and GenAI through an SDT theoretical lens illuminates the underlying factors that influence their LD choices and practice.

Utilising a quantitative ethnography (QE) approach and epistemic network analysis (ENA) (Shaffer, 2017), this research examines instructors' discussions when referring to LA versus GenAI as technologies that can support LD practice. By using ENA, we not only identify the factors that influence instructors' decision-making but also understand the relationship between the factors (Shaffer & Ruis, 2017). With this approach, we examined instructors' discussions relating to LA and GenAI use in LD practice. Recognising that LA and GenAI not only offer different capabilities but also different approaches to LD, our study informs the development of more effective LA and GenAI integration that aligns with instructors' naturalistic design practices.

Literature review

Learning design

Learning design is a complex domain situated in a particular academic context. The design process aims to create epistemic, social, and physical environments that facilitate students in reaching the intended outcomes (Goodyear et al., 2021). There is often a gap between learning designs and students' actual activities. These activities can only be imagined, and once implemented, students' autonomy influences the actual learning outcomes (Goodyear et al., 2021). Despite this, learning design has a strong influence on students' behaviour and ultimate academic success (Rienties & Toetenel, 2016). Therefore, it is important to understand instructors' design practices to create optimal conditions for instructors to flourish. Instructors' learning design practice is influenced by contextual aspects, such as university constraints (Bennett et al., 2011). Gaining insight into the contextual factors that influence learning design is essential for supporting instructors in making effective and responsive design decisions (Stefaniak & Xu, 2020).

In navigating LD complexity, LA provides instructors with information about student behaviour in a learning environment through the analysis of learner trace data, enabling them to make adjustments to their designs (Lockyer et al., 2013). It also provides instructors with valuable insights during reflective practice, helping them understand student engagement and make informed decisions about student support (Wise & Jung, 2019). To align with instructors' practices, it is important to consider how they navigate design and iterative adaptations. For this reason, Wang and Law (2025) emphasised the importance of LD granularity. LD granularity refers to the different levels of design (i.e., curriculum level, course level and task level). The curriculum component refers to the

learning outcomes targeted and the topics that enable the attainment of these outcomes. The course level refers to the aggregated course (a series of connected learning events), while the task level refers to individual tasks (i.e. a single learning event) and access to resources (Law & Liang, 2020). For example, OULDI (Rienties & Toetenel, 2016) conducted research on the task level and found that communication activities had a positive impact on student success. In a follow-up study at OULDI, collaborative activities proved difficult for tutors to maintain due to student resistance (Nguyen et al., 2022). These findings highlight the complexity underpinning learning processes. To support educational practice, GenAI is increasingly being used to suggest ideas for learning outcomes and topics (Divjak et al., 2025) and to provide personalised support to students, as well as to support instructional scaffolding (Bahroun et al., 2023). However, GenAI use also faces significant challenges around academic integrity, bias, ethics and the impact on student critical thinking. Hence, it is crucial to understand how GenAI can be effectively, ethically, and strategically implemented to support teaching and learning (Bearman et al., 2023).

Many LA and GenAI research studies overlook the learning outcomes, pedagogical approach, context, and subject matter (Topali et al., 2024). Thus, understanding the educational potential of both LA and GenAI requires holistic approaches that consider instructors' contextual considerations rather than treating LA and GenAI as isolated technologies. Human-centred approaches are necessary to fully understand how LA and GenAI can support LD. While considerable progress has been made in utilising LA to inform design practices, the impact has not yet reached its full potential due to research predominantly focusing on the technology (Dawson et al., 2019). However, as posited by Buckingham Shum et al., (2019), integrating technologies into practice is not only a technical endeavour but also a multidimensional human challenge influenced by leadership (Dawson et al., 2018). Stakeholder uptake can be unequal and exacerbated by individuals' emotional and cognitive dimensions, along with their contextual circumstances, constructs within Self-Determination Theory (SDT), which can help explain how instructors choose to use LA and GenAI to support their LD.

Self-determination theory

SDT is a motivational theory that encompasses the innate psychological need of people for *autonomy*, *competence* and *relatedness* (Deci & Ryan, 1985). *Autonomy* encompasses an individual's ability to make decisions freely that are self-endorsed and free from external interference; *competence* involves one's perception of mastery and effectiveness, and *relatedness* concerns the quality of interpersonal connections (Deci & Ryan, 2000). When these basic needs are met, individuals can grow and exhibit psychological well-being (Deci & Ryan, 2000). Conversely, contexts that hinder autonomy, competence, or relatedness result in diminished motivation and compromised well-being (Deci & Ryan, 2000). The theory has demonstrated broad applicability across various contexts, including higher education and LD. Given the role of motivation in professional performance, understanding how these psychological needs influence instructors in educational settings is critical and an under-researched area.

Psychological needs are fundamental to educational contexts because instructors' psychological needs satisfaction produces cascading benefits for student learning environments. For example, the relationship between instructor motivation and

autonomy-supportive practices represents a significant mechanism through which educators can foster students' psychological need satisfaction (Ryan & Deci, 2020). When instructors both value a task and experience agency in that task, they experience deeper, more positive emotions, such as enjoyment, contentment, and pride (Thies & Kordts-Freudinger, 2019). University instructors who are intrinsically motivated towards teaching tend to be less controlling and more autonomy-supportive towards students (Yasué et al., 2019). Aelterman et al. (2019) expand this conceptualisation by distinguishing between two principal components of autonomy-supportive teaching: i) offering students choices and ii) finding ways to understand and accommodate students' perspectives. In LD, autonomy support, competence support, and relatedness support principles can lead to increased student engagement and motivation (Martin et al., 2018). Autonomy-supportive design in MOOCs, for example, can be achieved by minimising reliance on rigid deadlines, offering meaningful choice, and reducing emphasis on controlling rewards (Martin et al., 2018). Understanding and supporting instructors' psychological needs becomes essential for creating LDs where SDT teaching practices can flourish and thereby benefit student learning.

Research questions

The literature review highlighted the significance of LD design on student outcomes and the potential of LA and GenAI in enhancing LD. To progress the LD field, a nuanced understanding of how LA and GenAI can be strategically applied is needed. Understanding instructors' discussions is essential because it illuminates the gap between technological potential and actual implementation, helping researchers and institutions develop more effective support strategies that align with instructors' lived experiences and needs. Therefore, this study aims to identify the factors that influence LD decision-making and practice in the context of LA and GenAI, investigated through the following research questions:

- RQ 1: How do factors that influence LD in the context of LA associate with each other?
- RQ 2: How do factors that influence LD in the context of GenAI associate with each other?
- RQ 3: What are the similarities and differences between the factors that influence LD in the context of LA and GenAI?

Methodology

Study methodology

To understand the complexity and nuance inherent in instructors' decision-making processes, while enabling the exploration of potential contradictions and tensions within their reported experiences, we collected qualitative data through a focus group study (Kamberelis & Dimitriadis, 2013). Our primary goal was to gain a deeper understanding and obtain additional warrants and evidence, rather than generate generalisable findings (Damşa & Barany, 2023). To do this, we adopted a QE approach (Shaffer, 2017). QE integrates qualitative and quantitative methods to gain a better understanding of discourse and, thereby, culture. Specifically, we employed Epistemic Network Analysis (ENA) (Shaffer, 2017), a widely used qualitative research methodology for understanding discourses. By using ENA as the analysis methodology, it is possible to identify and visualise

persistent patterns in the data (Damşa & Barany, 2023). Data were collected through focus groups with instructors regarding their use of technology in LD. The participants consisted of university instructors employed at a large public Australian university, all of whom taught within one faculty, either pre-service teacher education programs or tertiary preparation enabling programs, to ensure consistent leadership.

Study procedure

The study commenced after obtaining institutional ethical approval. To recruit instructors with relevant expertise in technology-informed course design, we employed a purposive sampling methodology (Merriam & Tisdell, 2016). Recruitment invitations were distributed via email to instructors, asking those with experience using LA (i.e., who had previously used the institutional LA dashboard) to participate in the LA focus group. The same invitation process was used for the GenAI focus group, requesting participation from instructors who had utilised GenAI (i.e. ChatGPT or Claude) to inform their LD practice. Six focus groups, comprising a total of 21 participants, explored LA-informed decision-making, while five focus groups, involving a total of 18 participants, explored GenAI-informed practices. Group composition ranged from two to five participants to optimise both intimate discussion and diverse perspectives. A total of 14 participants attended both the LA and GenAI focus groups. Each session was conducted online, using Zoom, ranging between 45 and 60 min under the guidance of an experienced moderator to ensure systematic data collection. The focus group discussions were structured by using focus group guiding questions (Appendix A). The focus groups were recorded and subsequently professionally transcribed and checked by the first author for accuracy.

Data analysis

The data analysis was performed in three phases: (1) thematic analysis and the creation of a codebook, (2) co-coding of the two groups (LA focus groups and GenAI focus groups) based on the Codebook, and (3) ENA analysis.

Thematic analysis and creation of a code book

Phase 1 involved a thematic analysis using qualitative coding analysis, as described by Saldaña, (2021). The first cycle analysis employed In Vivo qualitative codes, which were created by using words provided by participants to preserve their meaning, in combination with the level of meaning segmentation. The In Vivo coding resulted in 339 codes across the LA groups and 195 initial codes across the GenAI focus groups. Using participants' language meant the research language remained close to and was interpretable by the community it was intended for (Saldaña, 2021). The second cycle coding involved Pattern Coding, meaning codes were grouped into categories. The Codebook was developed by drawing on these categories and refining them through constant comparative analysis across the GenAI and LA groups (Boeije, 2002). The final list of codes included in the Codebook and subsequently used for the data co-coding and ENA analysis is shown in Table 1.

Table 1 LA Topic Kappa

Code	Coder 1 N	Coder 2 N	Agreement %	κ
Off-topic	1010	1299	68.60	0.121
CTX	1469	1379	64.90	0.140
D.AUTO	82	95	98.58	0.592
COURSE	815	956	72.49	0.059
CPS	1234	1025	68.04	0.090
ACT	313	314	90.48	0.192
ASSESS	339	320	89.12	0.118
TECH	335	385	93.79	0.536
D.SDT	134	71	96.21	0.061
SUPP	180	311	92.09	0.157
I.E	38	67	98.34	0.202

Table 2 GenAI Topic Kappa

Code	Coder 1 N	Coder 2 N	Agreement %	κ
Off-topic	89	77	93.69	0.616
CTX	278	382	73.23	0.426
D.AUTO	23	11	97.39	0.282
COURSE	50	41	95.10	0.480
CPS	144	113	80.74	0.201
ACT	82	35	91.84	0.323
ASSESS	141	210	85.53	0.536
TECH	322	342	81.07	0.590
D.SDT	148	56	83.46	0.183
SUPP	42	36	97.82	0.732
I.E	22	14	97.17	0.264

Coding of the focus group data

During Phase 2, the transcript data were segmented at the sentence level by the first author. The first two authors coded all focus group transcripts, one focus group at a time. Table 1 shows Cohen's Kappa for all LA focus groups combined, while Table 2 shows Cohen's Kappa for all GenAI Focus groups combined. All tables below show Cohen's Kappa calculated on combined datasets (all focus groups merged together for each grouping).

All data were coded in their entirety by two independent coders, with disagreements resolved through social moderation (Shaffer, 2017). The final agreement decisions were made by referring to the established Codebook definitions as shown in Table 3, and iterations to the Codebook were made to reflect the changes. The final coded data, reflecting 100% agreement obtained through social moderation, were used for the ENA.

Table 4 shows an example of the coded data with the moving window (MW) example indicating a five-line length unit.

The ENA analysis

Phase 3 involved the application of ENA analysis. The application of ENA to instructor discourse about GenAI and LA enables examination of the complex ways educators discuss their design practice. The strength of ENA lies in its capacity to model the structural connections within data, capturing not only the meaningful features (codes) present in conversations but also the patterns of co-occurrence that show how these features interrelate (Shaffer, 2017). By quantifying the co-occurrence of codes within

Table 3 The developed Codebook based on In Vivo thematic analysis

Code (abbreviation)	Description and example
Contextual information (CTX)	A statement that describes instances where information or an evaluation is obtained across areas such as students, tutors, pedagogy, knowledge about technology, other courses or programmes "So we really had to understand the graduate qualities, we wanted to get beyond just what students are to know and what they're able to do, as in knowledge and skills"
Course design decision making Autonomy (D.AUTO)	This code captures utterances about the influences of power in LD, including government regulations, institutional policies, policy bottlenecks, leadership dynamics, and technological constraints that impact instructors' autonomy and decision-making "And we had sort of the trust of our leaders that we were then becoming the experts in the area"
Course level design (COURSE)	A statement that describes course-level conceptual framing, including alignment with learning outcomes and sequencing of content "I do a conceptual framing of what the course needs to be in order to meet the objectives with the materials that I am knowledgeable about and have access to"
Creative problem solving (CPS)	The code describes dynamic and collaborative nature of course design, inquiry, problem-solving, creative design, human decision-making, use of external resources, co-design and co-review processes, and participation in communities of practice "have people to bounce those ideas off and to help take abstract sort of throw away thoughts and help get them into something that can be really valuable for the students."
Learning activity design (ACT)	A statement that describes activity design or redesign "I like to try to create activities that are not only helpful, but easy to engage with the students and like interactive, like H5P"
Assessment design (ASSESS)	The code captures utterances related to the design and redesign of formative and summative assessments "And then you have to think also with the assessment design, and then how that links through"
Technology role (TECH)	Instructors active or passive use of technology (LA or GenAI) or using technology to learn about technology "I've used feedback practices and things like OnTask very highly"
Design approach, design for student self-determination (D.SDT)	Utterances that describe LD for student Autonomy, Competence or Relatedness "I want to do something that's really a co-constructed, co-led course where the students are partners, as opposed to just students"
Student support (SUPP)	A statement encapsulating support either through personalisation, feedback or scaffolding "So for me it's about, thinking about how I'm going to scaffold the students across the semester"
Instructor emotion (I.E)	A statement encapsulating an instructor's affective state, negative or positive "And yeah, most of the time, the data is a bit sad."
Off-topic (OFF)	Statements unrelated to the case study "Scissors, paper, rock, maybe?"

conversations, ENA generates weighted networks of these relationships, accompanied by visualisations. All networks are analysed simultaneously, enabling both visual and statistical comparisons across the dataset. Although initially developed to study epistemic games, the ENA method has been applied in other domains. For example, student task performance (D'Angelo et al., 2020) and making sense of teacher agency (Pantić et al., 2022) were both examined using ENA methodology. The key assumption of the method is that the structure of connections in the data is meaningful (Shaffer, 2017). ENA is thus a valuable technique for modelling educational decision-making, as it can model the relationships among LA and GenAI use in LD decision-making as they occur within an LD community.

We applied ENA to examine the co-occurrences of codes in the focus group discourse (Shaffer & Ruis, 2017). The analysis was conducted using the ENA Web Tool (version 1.7.0) (Marquart et al., 2021). We defined the units of analysis as all lines of data

Table 4 Extract of the coded data and moving window example

Theme	Group	Person	Speaker	Off-topic	CTX	D	Autonomy	COURSE	CPS	ACTIVITY	ASS		Support	Unit		Unit
											RD	TECH		MW	MW	MW
AI	AIFG03	FG3 p4	So it can be quite good if you write a pretty good prompt and quite a lengthy prompt and tell it's an expert and all those kind of things	0	0	1	0	0	0	0	0	1	0	0	✓	
AI	AIFG03	FG3 p4	But it really is just a starting point, I think it's, you can't just go it's done me a lesson plan, brilliant, I'm off down to the pub	0	0	0	0	0	0	1	0	1	0	0	✓	✓
AI	AIFG03	FG3 p4	You've got to take that and then play around with it quite a lot, which, as FG3 p1 was saying, we're the experts in the room	0	0	0	0	0	1	0	0	1	0	0	✓	✓
AI	AIFG03	FG3 p4	But as an assistant, I think AI can be extremely useful in learning design, I think	0	0	0	0	1	0	0	0	1	0	0	✓	✓
AI	AIFG03	FG3 p4	Gets rid of a lot of those boring tasks that can take some time	0	0	1	1	1	0	0	0	1	0	0	✓	✓
AI	AIFG03	FG3 p4	You can kind of brainstorm with it a little bit, come up with activity types, come up with the lesson plans and so forth	0	0	0	0	0	1	0	0	1	0	0	✓	✓
AI	AIFG03	FG3 p4	So less about the actual expert content, but the way in which you can actually lay things out can work really, really well, I think	0	0	0	1	1	0	0	0	1	0	0		✓

(segmentation was performed at the sentence level) associated with a single value of theme, subsetting by focus group and theme (i.e., LA and GenAI). The ENA algorithm uses a moving window to construct a network model for each line in the data, showing how codes in the current line are connected to codes that occur previously (Siebert-Evenstone et al., 2017). We defined the moving window to consist of five lines (each line plus the four previous lines), because five lines encapsulated the necessary context within the coded data following a unit of meaning qualitative analysis (Siebert-Evenstone et al., 2017). Four additional window lengths ranging from three to seven were analysed to compare the results with the selected five lines. To assess how sensitive the ENA results are to the choice of moving-window lengths, four additional window lengths (three, four, six, and seven lines) were analysed to compare the results with the initial 5-window analysis. The lines were compared using co-registration correlations to assess the goodness of fit between the visualisation and the original high-dimensional model as window length varies, and Mann–Whitney *U* tests, which assess whether the observed difference between the Learning Analytics (*N*=21) and Artificial Intelligence (*N*=18) lies along each dimension. The results showed consistency across window lengths 3–7 (Table 5).

In addition, the selected window size aligns with Shaffer's (2017) recommendation stating that five is an appropriate window size for discussion data which aligns with this study design. The resulting networks are aggregated for all lines for each unit of analysis in the model. In this model, we aggregated networks using a binary summation in which the networks for a given line reflect the presence or absence of the co-occurrence of each pair of codes. Alternative models were tested using three alternative weighted transformations, Square Root, Natural Log and Product (Appendix B). Plots and network visualisations were interpreted through a qualitative lens based on the initial qualitative analysis, thereby adding interpretive meaning to the underlying code co-occurrences beyond what the statistical output alone can convey (Shaffer, 2017). The last code in the Codebook, Off-topic, was excluded during analysis. We defined conversations as all lines of data associated with a single value of a theme subsetting by the group. For example, one conversation consisted of all the lines associated with a single theme (e.g., Learning Analytics) and a specific group (e.g., LAFG01).

The ENA model normalised the networks for all units of analysis before they were subjected to a dimensional reduction, which accounts for the fact that different units of analysis may have different numbers of coded lines in the data. For the dimensional

Table 5 Window length overview range

Win-dow length	Variance dimension 1 co-registration correlations	Variance dimension 2 co-registration correlations	Mann–Whitney <i>U</i> test X axis (SVD 1)	Mann–Whitney <i>U</i> test Y axis (SVD 2)
3 lines	0.94 (Pearson) and 0.94 (Spearman)	0.96 (Pearson) and 0.96 (Spearman)	<i>U</i> = 375.00, <i>p</i> < 0.001, <i>r</i> = − 0.98	<i>U</i> = 154.00, <i>p</i> = 0.34, <i>r</i> = 0.19
4 lines	0.95 (Pearson) and 0.95 (Spearman)	0.97 (Pearson) and 0.96 (Spearman)	<i>U</i> = 373.00, <i>p</i> < 0.001, <i>r</i> = − 0.97	<i>U</i> = 200.00, <i>p</i> = 0.77, <i>r</i> = − 0.06
5 lines	0.96 (Pearson) and 0.96 (Spearman)	0.96 (Pearson) and 0.96 (Spearman)	<i>U</i> = 370.00, <i>p</i> < 0.001, <i>r</i> = − 0.96	<i>U</i> = 200.00, <i>p</i> = 0.77, <i>r</i> = 0.06
6 lines	0.96 (Pearson) and 0.96 (Spearman)	0.97 (Pearson) and 0.97 (Spearman)	<i>U</i> = 368.00, <i>p</i> < 0.001, <i>r</i> = − 0.95	<i>U</i> = 209.50, <i>p</i> = 0.57, <i>r</i> = − 0.11
7 lines	0.97 (Pearson) and 0.97 (Spearman)	0.97 (Pearson) and 0.97 (Spearman)	<i>U</i> = 368.00, <i>p</i> < 0.001, <i>r</i> = − 0.95	<i>U</i> = 204.00, <i>p</i> = 0.69, <i>r</i> = − 0.08

reduction, ENA uses a singular value decomposition (SVD), which produces orthogonal dimensions that maximise the variance explained by each dimension (Bowman et al., 2021). Networks were visualised as network graphs, where nodes represented codes and edges indicated the relative frequency of co-occurrence between two codes. Each unit of analysis was shown both as a plotted point marking the location of that unit's network in a low-dimensional projected space and as a weighted network graph. Node positions within the network graphs were fixed using an optimisation routine that minimised the distance between plotted points and their corresponding network centroids. Because the network graphs and projected space are co-registered, the positions of nodes and their connecting edges can be used to interpret the dimensions of the projected space and explain the locations of plotted points (Bowman et al., 2021). In the present analysis, means rotation was not performed because preliminary examination revealed that group means were already well-aligned along the X-axis of the original SVD space. Given this existing alignment, additional means rotation would not have provided meaningful improvement to group separation or interpretability of the dimensional space.

ENA can be used to compare units of analysis in terms of their plotted point positions, individual networks, mean plotted point positions, and mean networks, which average the connection weights across individual networks. To understand how the GenAI discourse and LA discourse in LD compare, we compared our networks using network difference graphs. For this purpose, the subtraction network (Fig. 4) was calculated by subtracting the weight of each connection in the LA network from the corresponding connections in the GenAI network. To test for differences, we applied a Mann–Whitney U test to the locations of points in the projected ENA space for units in the LA group and the AI group.

Results

The results indicate that the visualisation of the model had co-registration correlations of 0.96 (Pearson) and 0.96 (Spearman) for the first dimension and co-registration correlations of 0.96 (Pearson) and 0.96 (Spearman) for the second. These measures indicate a strong goodness of fit between the visualisations and the original model. The results of the Mann–Whitney U test indicate a significant difference between the AI and LA discussions on SVD 1, but not on SVD 2, as shown in Fig. 1. This figure indicates the locations of the points of the projected space along the X (SVD 1) and Y axis (SVD 2). Along the X axis (SVD 1), the Mann–Whitney U test showed that the LA group ($Mdn = -0.23$, $N = 21$) was significantly different from the GenAI group ($Mdn = 0.32$, $N = 18$, $U = 370.00$, $p < 0.001$, $r = -0.96$). Along the Y axis (SVD 2), the Mann–Whitney U test showed that the LA discussion ($Mdn = 0.04$, $N = 21$) was not significantly different from the AI discussion ($Mdn = -0.05$, $N = 18$, $U = 200.00$, $p = 0.77$, $r = 0.06$). Figure 1 indicates the combined LA and GenAI visualisation in the projected space. The LA centroid is positioned on the left, and the GenAI centroid is positioned on the right.

RQ 1: How do factors that influence decision-making in the context of LA associate with each other?

The network demonstrates the connection strength among the themes. The strongest connections are observed between contextual information and technology role (CTX and TECH: 0.32), contextual information and course level design (CTX and COURSE:



Fig. 1 ENA Subtraction graph between LA theme (red on the left) and GenAI theme (blue on the right). The comparison plot was created using the binary model

0.23), and contextual information and creative problem solving (CTX and CPS: 0.32), forming the most densely connected clusters within the network. These themes show the highest co-occurrence rates, indicating that participants frequently discussed these concepts together when describing their LA decision-making processes. Moderate edge weights were found between technology role and learning activity design (TECH and ACT: 0.17), between student support and technology role (SUPP and TECH: 0.19), and between decision-making autonomy and context (D.AUTO and CTX: 0.14). Weaker connections include several pairings with lower co-occurrence rates: technology role and course level design (TECH and COURSE: 0.11), technology role and course design decision-making power (TECH and D.AUTO: 0.07), technology role and assessment redesign (TECH and ASSESS: 0.08) and technology role and design for student self-determination (TECH and D.SDT: 0.09). While these connections are less prominent in the discourse, they represent less frequently articulated relationships in instructors' decision-making discussions. The network structure suggests that instructors' discourse about LA centres primarily revolves around the intersection of contextual considerations, course design requirements, and creative problem-solving approaches. This is evident in the triad contextual information and technology role (CTX and TECH: 0.32), contextual information and course level design (CTX and COURSE: 0.23), and contextual information and creative problem solving (CTX and CPS: 0.32), suggesting that instructors actively use LA in combination with contextual information when engaging in creative problem-solving at the course level. Figure 2 presents the average epistemic

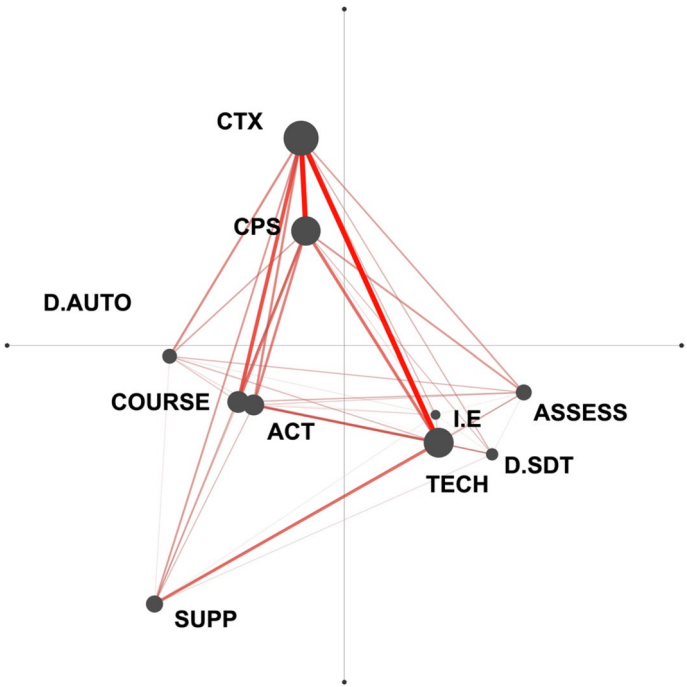


Fig. 2 ENA Subtraction graph between LA theme (red on the left) and GenAI theme (blue on the right). The comparison plot was created using the Natural Log Weighted Model

Table 6 ENA co-occurrence edge strengths for the Learning Analytics theme

Code pair	Weight
CTX and CPS	0.32
CTX and TECH	0.32
CTX and COURSE	0.23
SUPP and TECH	0.19
TECH and ACT	0.17
D.AUTO and CTX	0.14
TECH and COURSE	0.11
TECH and D.SDT	0.09
TECH and ASSESS	0.08
TECH and D.AUTO	0.07

network for all participants from LA focus groups. Table 6 indicates the edge weights for the LA focus group network, ordered by strength.

RQ 2: How do factors that influence decision-making in the context of GenAI associate with each other?

The network indicates the strongest connections between the following themes: contextual information and creative problem solving (CTX and CPS: 0.26), technology role and assessment design (TECH and ASSESS: 0.26), and technology role and design for student self-determination (TECH and D.SDT: 0.15). This dense interconnection suggests that participants frequently discussed these concepts together when considering the implementation of GenAI in their LD processes. Moderate connections form the second tier of associations, particularly between learning activity design and technology role (ACT and TECH: 0.15) and between technology role and course level design (TECH and COURSE: 0.14). These relationships indicate secondary but meaningful conceptual

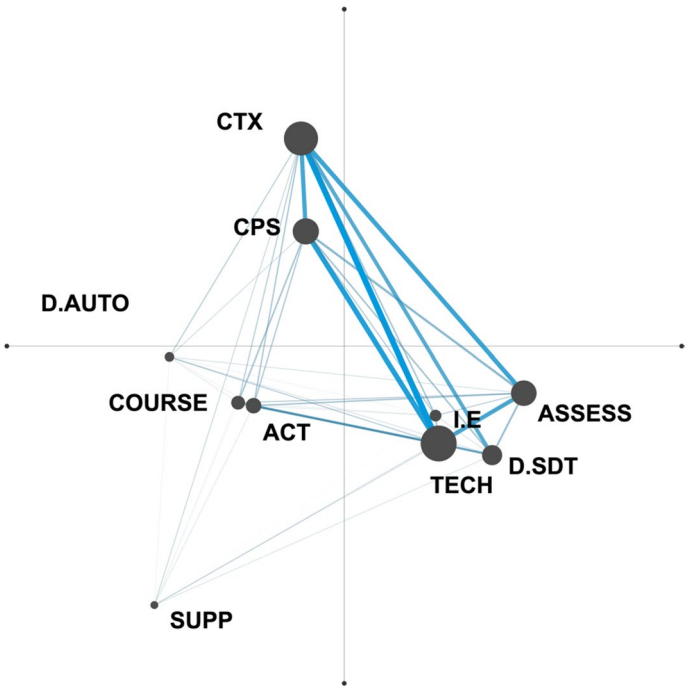


Fig. 3 ENA Subtraction graph between LA theme (red on the left) and GenAI theme (blue on the right). The comparison plot was created using the Product Weighted Model

Table 7 ENA co-occurrence edge strengths for the GenAI theme

Code pair	Weight
CTX and CPS	0.26
TECH and ASSESS	0.26
TECH and COURSE	0.14
TECH and D.SDT	0.15
ACT and TECH	0.15
D.AUTO and TECH	0.06
TECH and SUPP	0.03
D.AUTO and SUPP	0.01

linkages in instructors’ discussions about GenAI. Weaker connections are observed between LD decision-making power and technology (D.AUTO and TECH: 0.06), as well as between course design decision-making power and student support (D.AUTO and SUPP: 0.01). Notably, the connection between the technology role and student support (TECH and SUPP: 0.03) demonstrates minimal co-occurrence, suggesting that instructors rarely discuss these concepts together when considering GenAI applications in their design practice. The network reveals that instructors’ GenAI discourse mainly focuses on contextual information and assessment redesign. Figure 3 presents the average ENA network derived from the combined GenAI focus group data, revealing the patterns of association between factors. Table 7 presents the connection weights for the GenAI focus group epistemic network, ranked by strength.

RQ3: What are the similarities and differences between the factors that influence LD in the context of LA and GenAI?

This subtractive network reveals distinct emphases and differences in how instructors discuss LA and GenAI. The plot shows stronger associations in the LA group for several key themes. The technology role demonstrates high co-occurrence with student support (TECH and SUPP: 0.16), indicating that instructors more frequently discussed student support in relation to LA than GenAI. Additionally, the LA discourse shows a stronger co-occurrence between technology role and course (TECH and COURSE: -0.03), LD decision-making autonomy and technology (D.AUTO and TECH: 0.01), and activity design and technology (ACTIVITY and TECH: -0.02). The instructor's emotion code had low co-occurrences with four ties. These are instructor emotion and decision-making autonomy (I.E and D.AUTO: 0.01), instructor emotion and activity (I.E and ACT 0.02), instructor emotion and support (I.E and SUPP: 0.02).

In contrast, the GenAI group exhibits stronger associations between technology role and assessment design (TECH and ASSESS: -0.18) and between technology role and design for student self-determination (TECH and D.SDT: -0.06). Instructor emotion had low co-occurrences, with five ties within GenAI: Instructor emotion and assessment (I.E and ASSESS: -0.04), instructor emotion technology (I.E and TECH: -0.03), instructor emotion and creative problem solving (I.E and CPS: -0.03), and instructor emotion and design for student self-determination (I.E and D.SDT: -0.01). The co-occurrence of creative problem-solving and technology was more prominent in GenAI discussions, although creative problem-solving maintained a central position across both groups (CPS and TECH: -0.13). This pattern suggests that when discussing GenAI, instructors more frequently consider GenAI in relation to assessment design and design approaches (i.e. student self-determination). The centrality of the CTX code across both networks, highlights the intricate nature of LD when drawing on LA and GenAI.

Figure 4 illustrates the subtraction network comparison between GenAI and LA, highlighting the differences in themes and connections.

Discussion

This study examined the factors influencing instructors' LD decision-making and practice when integrating LA and GenAI into their LD practices. Drawing on a thematic analysis of focus group discussions and ENA, we investigated how instructors discuss LD in relation to GenAI and LA, and identified factors that influence LD practice. While both technologies offer powerful capabilities for enhancing LD practice, instructors' adoption decisions are shaped by multiple intersecting factors, including their emotions, creative problem-solving skills, perceptions of their autonomy, and contextual considerations. Their LD decisions and practices related to building their students' self-determination, iteratively enhancing their LD at the course and activity levels, and better supporting their students and designing assessment tasks. Combined, these factors provide an understanding of instructors' lived experience when utilising LA and GenAI, and offer insight into instructors' LD decision-making. Our analysis reveals distinct patterns of reasoning that characterise instructors' use of LA versus GenAI, illuminating complex dynamics that influence technology integration in higher education. The following sections present our results systematically by research question.

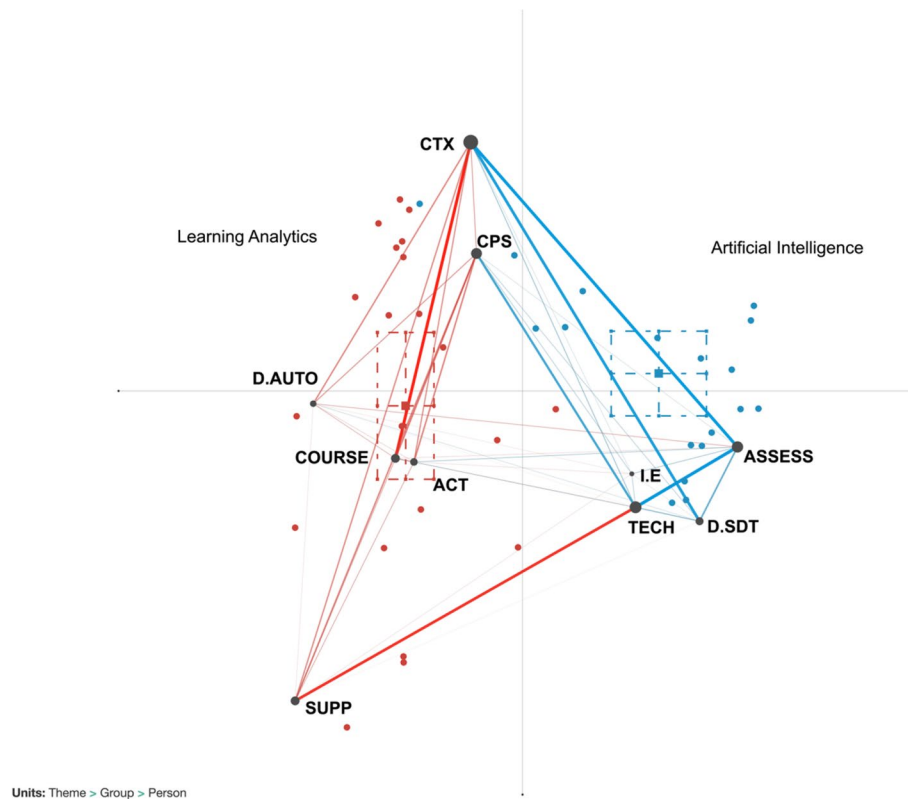


Fig. 4 ENA Subtraction graph between LA theme (red on the left) and GenAI theme (blue on the right). The comparison plot was created using the Square Root Weighted Model

RQ 1: How do factors that influence learning design in the context of LA associate with each other?

The ENA revealed that instructors approached the use of LA to support their problem-solving by drawing on LA (i.e. teaching dashboards) in tandem with information about their educational context to build a holistic picture of the changes they would make to their LD. When discussing LA, the ENA results indicate that instructors spoke most frequently about contextual considerations, course design, and creative problem-solving approaches. The prominence of contextual considerations in instructor discussions reflects the broader recognition that LA cannot be meaningfully interpreted without understanding the pedagogical intent (Lockyer et al., 2013). This highlights the importance of the educational context on instructors' decisions.

In the LA discussions, the instructors often referred to activity design (ACT) and student support (SUPP), and their educational context influenced their autonomy in decision-making. Leadership LD decision-making autonomy refers to instructors' capacity to make choices about their LD practices based on their LD expertise, design approach, and within the external mandates or systemic constraints. While constraints cannot be avoided, complexity leadership approaches can help navigate tensions arising from environmental pressure (Dawson et al., 2018). This approach gives instructors shared autonomy in institutional decision-making.

Co-occurrence in the discussions highlights LA's value in identifying where students need additional support as well as designing supportive scaffolds. In a study by Lim et al. (2023), instructors most often used LA data to identify where students were struggling,

allowing them to provide personalised feedback. Our findings show that most instructors talk about different levels of course granularity (i.e. course level, activity level, student support) when making use of LA to improve their LD. The LA-informed LD practices of the instructors strongly support the findings of Law and Liang (2020), suggesting the need for multilevel structures that recognise that LD operates at different levels, from broad learning outcomes down to specific activities. In our study, instructors made iterations to their activities based on trace data. These findings show that instructors rely on LA and contextual information to inform their creative problem-solving related to their course design, individual activities, and student support.

RQ 2: How do factors that influence learning design in the context of GenAI associate with each other?

The ENA identified strong co-occurrences between GenAI (TECH) and assessment design (ASSESS) as well as GenAI (TECH) and design for student self-determination (D.SDT). Instructors created first drafts of assessment elements (i.e. case studies and rubrics) using GenAI. This echoes the findings of a recent systematic review where Nikolic et al. (2024) found that instructors value GenAI for creating assignments and tests. The use of SDT as an learning design framework has been suggested by Martin et al. (2018), where design elements are organised around autonomy, competence and relatedness. In our study, the design for student self-determination was evident as an instructional approach, where student autonomy, for example, was considered by co-designing course elements with students. Ryan and Deci, (2020) state that autonomy is best facilitated when students are provided with meaningful choices and when learning tasks align with their personal interests and values. For example, in our study, instructors co-designed assessment rubrics with students in initial teacher education (i.e. pre-service teachers), scaffolding their competence in learning design and providing them with autonomy over their learning experience. Similarly, Zheng et al. (2020) found that the opportunity for students to contribute to the creation of assessment rubrics increased their motivation.

However, there was less co-occurrence of GenAI (TECH) and course level (COURSE). This can be attributed to a range of factors, such as instructors stating that they value backward design and constructive alignment, yet not mentioning the use of GenAI for this purpose. Divjak et al. (2025) found similar adoption patterns, where instructors tend to trust GenAI more in the design of units and activities, as well as in generating ideas, rather than for generating topics and learning outcomes. Similarly, the ENA results showed low co-occurrence between GenAI (TECH) and student support (SUPP), as well as between GenAI (TECH) and decision-making autonomy (D.AUTO). This suggests that when instructors discussed GenAI, they rarely focused on how it could enhance student support or how the extent of their autonomy affected their LD decisions. Instead, instructor discussions were primarily focused on assessment design in relation to their design approach. In addition, instructors' sense of LD agency was more influenced by their educational context than by GenAI.

RQ 3: What are the similarities and differences between the factors that influence LD in the context of LA and GenAI?

Across both LA and GenAI outcome networks, the co-occurrence of technology role (TECH), contextual information (CTX), and creative problem solving (CPS) was high. This indicates that instructors drew on LA and GenAI in combination with contextual considerations and course design requirements to solve instructional problems, utilising their creativity and collaborating with colleagues. Similarly, Toetenel and Rienties (2016a, 2016b) found that collaboration during workshops made learning design more creative and student-centred. Prioritising collaboration could yield positive benefits, as this supports the need for relatedness, a key SDT construct. In addition, co-design processes can provide an opportunity to develop LD competence as a community of practice, building on each other's skillsets and through conversations that unpack contextual considerations, thereby fostering instructors' relatedness, another key SDT construct. According to SDT, supporting autonomy, relatedness, and competence is critical for need satisfaction (Ryan & Deci, 2020), which is a significant predictor of favourable work outcomes, including enhanced performance and better workplace adaptation (Baard et al., 2004). These findings highlight the importance of creating a supportive environment for instructors (Varga-Atkins et al., 2021).

Interestingly, instructor emotion (I.E) was linked to various codes across both LA and GenAI networks. The creative nature of LD means that initial attempts may require multiple iterations, requiring emotional resilience (Sharpe et al., 2022). While instructor emotion was evident in both LA and GenAI focus groups, the GenAI discussion elicited a more emotional response from instructors. From an SDT perspective, both positive and negative emotions can aid sensemaking and inform choices (Roth et al., 2019), and recognising instructors' emotional dimensions is essential to the iterative design process. Giving instructors the opportunity to explore a full range of emotions without judgment or trying to control their emotional responses, either by an external party (i.e., support staff, university leadership) or by the instructors themselves, could lead to better integrative emotional regulation, resulting in enhanced decision-making and creativity.

Implications

We identified the following factors that influence instructors' LD when integrating LA and GenAI: contextual information, course design decision-making autonomy, creative problem solving, learning activity design, assessment design, design approach (i.e. design for students' self-determination), and student support. Instructors can draw on the affordances of LA and GenAI in combination with the aspects identified in this study enabling a holistic technology integrated approach (Nguyen et al., 2025). Keeping assessments current through the thoughtful use of GenAI supports academic integrity, LA-informed decision-making, and alignment with students' learning needs. Using LA to understand engagement and GenAI to guide course and assessment redesign enables more proactive, student-centered support. For example when instructors assess course level analytics, instructors may identify patterns of student difficulty and subsequently leverage GenAI to help generate targeted support material (Bahroun et al., 2023). In addition, creative problem-solving emerges as a primary factor as instructors navigate the implementation of their educational intent while integrating information from learning analytics alongside contextual factors. Supporting psychological needs satisfaction

does not only benefits instructors' well-being (Thies & Kordts-Freudinger, 2019) but also provides better support for students (Yasué et al., 2019).

To support instructors' autonomy, competence, and relatedness in educational decision-making practice, universities can implement several key strategies. Firstly, from a leadership perspective it is important to ensure contextual and technology integration information flow across the institution in a transparent way. The exchange of design relevant networking can be facilitated by supporting collaboration. In addition, Tsai et al. (2020) suggest creating a culture of experimentation, brokering activities and networking opportunities. Collaborative design interventions have been shown to improve creativity (Toetenel & Rienties, 2016a, 2016b). Instructors' emotional well-being and motivation can be enhanced through collaborative design processes and communities of practice. Secondly, sharing decision-making between leadership and instructors with regards to GenAI integrity, course design policy and professional development would enable a better understanding of constraints and opportunities and allow a more robust co-ordinated effort. Dawson et al., (2018) describes recommendations for distributed leadership and shared decision-making at the institutional level. Involving instructors in decisions about LA and GenAI tool selection and implementation processes, and providing instructors with meaningful choices in how they integrate these technologies into their teaching practices. These collaborative environments support key psychological need-satisfaction aspects such as competence, by providing and receiving feedback and fostering relatedness.

Limitations and future studies

This research has several limitations that inform future work. First, participants were recruited from one faculty, consisting of instructors teaching in pre-service and enabling programs, from one large Australian university, through voluntary participation. In addition, there was an substantial overlap in participants across the LA and GenAI focus groups (14 of the participants contributed to both groups). The context of pre-service teaching influenced the results pertaining to participants engaging in co-design with their students, which may not necessarily transfer to other discipline contexts. Future studies could extend the scope of investigation beyond pre-service and enabling programs by including different disciplines and contexts to encompass a broader range of disciplines and institutional settings, thereby enhancing the generalisability of these findings. Second, the initial low pre-moderation K-values for certain codes (Tables 1 and 2) reflect initial uncertainty during independent coding. Notably, the codes D.AUTO and I.E. exhibited high raw agreement but disproportionately low kappa values, a pattern attributable to the low base rate of these codes rather than to substantive disagreement between coders (Feinstein & Cicchetti, 1990). The coding decisions involved subjective interpretation that may have influenced the results. In addition, ENA networks capture patterns in discourse, specifically, how frequently codes co-occur within the segments of talk analysed rather than direct observations of participant behaviour. Where the discussion draws connections between low or high co-occurrence and instructors' discussions, the interpretations should be understood as researcher inferences grounded in discourse patterns. A further limitation concerns the choice of aggregation method and ENA moving window used in the ENA model. This study employed binary aggregation and this

Table 8 Focus group guiding questions- LA

Data collection phase 1: LA
How do you go about course design?
How does data help your course design?
How does data influence your motivation?
Do you feel a sense of autonomy when you design?
Do you design as a collaborative process?

Table 9 Focus group guiding questions – GenAI

Data collection phase 2: GenAI
How are you learning about GenAI?
Have you made changes to your courses because of GenAI technologies like ChatGPT or BARD?
Are you currently using AI to help you design your course?
What barriers do you face when using AI in course design process?

approach does not account for the intensity or repetition of connections within a given unit of analysis.

Conclusion

This study examined instructors’ discussions concerning LD practice when integrating LA and GenAI. Drawing on thematic analysis of focus groups followed by ENA, we investigated how instructors navigate the evolving landscape of educational technology integration in their design practices. The ENA results demonstrated that LA discussions were characterised by co-occurrences between contextual considerations, course-level design, and creative problem-solving approaches, while GenAI discussions showed strong co-occurrences between assessment design, context, and design approaches (i.e., for student self-determination). Across both LA and GenAI networks, high co-occurrence patterns emerged between the technology’s role, contextual information, and creative problem-solving, indicating that instructors consistently combine technological affordances with contextual considerations and creative problem-solving. These findings reveal that instructors utilise LA for problem-solving, from broad course design to specific learning activities, assessment creation, and targeted student support. Meanwhile, instructors use GenAI for ideation and development of assessment elements, guided by their own design approach. Supporting instructors’ basic psychological needs —autonomy, competence, and relatedness — will foster creative problem-solving approaches in LD.

Appendix A

Table 8 outlines the guiding questions developed for the Learning Analytics (LA) focus group discussions.

Table 9 provides an overview of the guiding questions that structured the Generative Artificial Intelligence (GenAI) focus group.

Appendix B

Testing of window length sensitivity

Co-registration correlations were consistently strong across all window sizes. At a window size of three lines, the model had co-registration correlations of 0.94 (Pearson) and

0.94 (Spearman) for the first dimension, and 0.96 (Pearson) and 0.96 (Spearman) for the second dimension. At a window size of four lines, co-registration correlations were 0.95 (Pearson) and 0.95 (Spearman) for the first dimension, and 0.97 (Pearson) and 0.96 (Spearman) for the second. At a window size of six lines, co-registration correlations were 0.96 (Pearson) and 0.96 (Spearman) for the first dimension, and 0.97 (Pearson) and 0.97 (Spearman) for the second. Finally, at a window size of seven lines, co-registration correlations were 0.97 (Pearson) and 0.97 (Spearman) for the first dimension, and 0.97 (Pearson) and 0.97 (Spearman) for the second. These measures indicate a strong goodness of fit between the visualisation and the original model.

Results of the Mann–Whitney U test along the X-axis (SVD1) showed significant differences across all window sizes, including windows three, four, six, and seven. At a window size of three lines Learning Analytics (Mdn = −0.16, N = 21) was statistically significantly different at the $\alpha = 0.05$ level from Artificial Intelligence (Mdn = 0.26, N = 18 U = 375.00, $p < 0.001$, $r = -0.98$). This difference remained significant at window sizes of 4 lines (Mdn = 0.29, N = 18 U = 373.00, $p < 0.001$, $r = -0.97$), 6 lines (Mdn = 0.32, N = 18 U = 368.00, $p < 0.001$, $r = -0.95$) and 7 lines (Mdn = 0.32, N = 18 U = 368.00, $p < 0.001$, $r = -0.95$). These findings are similar to the significant difference found in the selected 5-window stanza.

In contrast, no significant difference was found along the X-axis (SVD2) at any window size. At a window size of three lines the Mann–Whitney test showed that Learning Analytics (Mdn = 0.11, N = 21) was not statistically significantly different at the $\alpha = 0.05$ level from Artificial Intelligence (Mdn = −0.07, N = 18 U = 154.00, $p = 0.34$, $r = 0.19$). Similarly, there were no significant differences across four lines (Mdn = 0.01, N = 18 U = 200.00, $p = 0.77$, $r = -0.06$), six lines (Mdn = −0.04, N = 18 U = 209.50, $p = 0.57$, $r = -0.11$) and seven lines (Mdn = −0.03, N = 18 U = 204.00, $p = 0.69$, $r = -0.08$). Having no significant difference across window sizes revealed a dimension-specific robustness in relation to the window stanza from 3 to 7 lines.

Testing of different weighted models

To test the robustness of the network structure produced by the primary ENA model, three alternative weighting transformations, Square Root, Natural Log, and Product, were applied to the same dataset and compared with the binary model selected as the baseline for this analysis. Across all four models, the underlying network structure was consistent. CTX, CPS, ASSESS, D.SDT and TECH defining the Artificial Intelligence (blue, on the right) side and CTX, ACT, COURSE, and SUPP defining the Learning Analytics (red, on the left) side. Figure 1 displays the comparison plot using the binary model. Figures 2, 3 and 4 are weighted models.

Abbreviations

LD	Learning design
ENA	Epistemic network analysis
GenAI	Generative artificial intelligence
HCLA	Human-centred learning analytics
LA	Learning analytics
OULDI	Open university learning design initiative
QE	Quantitative ethnography
SDT	Self-determination theory
SVD	Singular value decomposition

Acknowledgements

The authors express gratitude to all the participants for their involvement and cooperation in this study.

Author Contribution

Alrike Claassen: Conceptualisation, investigation, writing original draft, thematic analysis and Codebook development, co-coding of qualitative data, ENA analysis, editing. Daniel Ebbert: Co-coding of qualitative data, ENA analysis, editing. Vitomir Kovanović: Conceptualisation, ENA analysis, editing. Negin Mirriahi: Conceptualisation, editing. Shane Dawson: Conceptualisation, editing.

Funding

Not applicable.

Data availability

Not applicable.

Declarations**Ethics approval and consent to participate**

Ethics was obtained from the Human Research Ethics Committee. Ethics project number: 205282.

Competing interests

The authors declare no competing interests.

Received: 5 September 2025 / Accepted: 4 August 2026

Published online: 25 August 2026

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