From Data to Design: Integrating Learning Analytics into Educational Design for Effective Decision-Making

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Abstract

Learning Analytics (LA) aims to provide university instructors with meaningful data and insights that can be used to improve courses. However, instructors are often met with challenges that arise when wanting to use LA to inform their educational design decisions. For instance, there may be a misalignment between instructors' needs and the data and insights LA systems provide. Further research is required to understand instructors' expectations of LA and how it can support the diversity of educational designs. This case study addresses this gap by investigating the role of LA in instructors' educational decision-making processes. The study employs self-determination theory's constructs to examine instructors' existing practices when using LA to support their decision-making. The study reveals that LA enables instructors to make data-informed iterative educational design decisions, supporting their need for competence and relatedness. The emotional aspect of LA is an important consideration that can easily lead to demotivation and avoidance of LA. Support is needed to address instructors' psychological needs so instructors can fully utilise LA to make effective educational design decisions. The findings inform a framework for considering how instructors' data-informed educational decision-making can be understood. The implications of our findings and opportunities for the future are discussed.

CCS Concepts

• **Applied computing** → Education; Interactive learning environments; Education; E-learning.

Keywords

Learning analytics, data-informed decision-making, self-determination theory, educational design, higher education

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

ACM ISBN 979-8-4007-0701-8/25/03
https://doi.org/10.1145/3706468.3706541

ACM Reference Format:
Alrike Claassen, Negin Mirriahi, Vitomir Kovanović, and Shane Dawson. 2025. From Data to Design: Integrating Learning Analytics into Educational Design for Effective Decision-Making: From Data to Design. In *LAK25: The 15th International Learning Analytics and Knowledge Conference (LAK 2025), March 03–07, 2025, Dublin, Ireland*. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3706468.3706541

1 INTRODUCTION

Educational design is a central part of teaching practice. Goodyear et al. [15] posit that instructors take into consideration structure, social dynamics, and epistemology to inform the design of physical, social, and epistemic learning environments. *Physical design* relates to the design of the learning environment, the tools, and the artefacts. Similarly, *social design* refers to the design of student collaboration and the social climate where learning happens, while epistemic design refers to the design of the learning tasks students are expected to complete [15]. The educational design decision-making process is complex, and university instructors need relevant information on which to base their decisions. In the Higher Education context, this information is typically derived from student retention, academic outcomes and course evaluations. However, evaluation surveys are provided at the end of a course, limiting the usefulness of the information for more proactive real-time decisions.

The connection between Learning Analytics (LA) and educational design is well-established [2] [26] [36]. LA can provide actionable insights to inform instructors' decision-making, thus informing the implementation of support interventions and possible educational design changes [12]. For example, by combining measurement theory and LA, it is possible to evaluate the alignment between learning outcomes and assessments [4]. Educational design and LA are interconnected through teacher inquiry to enable an instructor to work towards an optimised educational design that is specific to the context of their teaching and learning practice [31].

To date, there has been limited consideration of how instructors utilise LA data for educational design decision-making to improve and inform their course design [45]. This is reflected in the primary use of LA for improving retention instead of improving course design and its alignment to discrete disciplinary contexts [33]. Moreover, SDT has been widely used in education settings, with more than 200 empirical studies drawing on the conceptual framing. However, most studies have focused on students, and there remains limited research examining an instructor's perspective [37] [16] [40]. To address this research gap, we explored instructors' use of LA to support their course design decision-making processes. We utilised Ryan and Deci's [39] Self-determination Theory (SDT) as a framework to understand instructors' data-informed design decisions through three dimensions: *autonomy* (in decision-making), *competence* (in getting LA feedback on design competence and feeling competent in making LA-informed decisions) and *relatedness* (to students and colleagues). By exploring how instructors perceive the role of LA in their decision-making process, this study adds to our understanding of instructors' needs and expectations regarding the role of LA in the course design and redesign cycle. Thus, the study provides directions for future LA tools and dashboard development and guidance for university support systems.

2 BACKGROUND

Instructor inquiry requires in-depth information processing to make decisions on the data in a meaningful way. The decision-making process is usually initiated by accessing LA dashboards and reports [50]. However, this approach assumes that instructors not only understand the presented data but can also interpret its meaning and apply it effectively in practice. In this context, the instructor's data literacy is paramount [27]. However, as Rienties et al. [35] demonstrated, LA dashboards and visualisations are often designed without considering the instructors' needs and data literacy skills. As a result, the potential impact and importance of the LA data are limited by the instructors' ability to interpret and make actionable use of the provided information [35]. Studies have shown that instructors appreciate hands-on workshops on LA but highlight the need for support and training as LA dashboards are often challenging to navigate and use [1] [35]. Data literacy among instructors and well-designed dashboards are crucial to effectively leverage the affordances LA can bring to teaching practice. The ability to effectively process and interpret LA is not only a cognitive task but also an emotional one. Instructors exhibit emotions ranging from positive responses, for example, "enjoyment", "surprise" and "curiosity", to adverse reactions, such as "disappointment", "confusion", and "frustration" [50] [53]. Expert instructors tend to exhibit more epistemic emotions than novice instructors [53]. An instructor's emotional reaction to analytics is an important consideration in educational design decision-making and warrants further exploration. The accurate interpretation of data first involves gaining a sense of the overall trends before focusing on specific data items that can inform teaching decision-making [23]. Wise and Jung [50] reported instructors' decisions in response to analytical insights varied, including comprehensive scaffolding for the entire class, focused scaffolding for students based on needs, and amendments to the course educational design.

Self-determination theory (SDT) [39] posits that people thrive when their basic needs for autonomy, competence, and relatedness are met. SDT distinguishes between *self-determined behaviour* – driven by intrinsic motivation, and *automatic behaviour*, which is more reactive and externally based [9]. Individuals experience increased intrinsic motivation and engagement when situated in an environment that fosters their psychological need for *autonomy*, *relatedness* and *competence*, leading to improved performance when these needs are met (labelled as *Need Satisfaction* in SDT theory). *Autonomy* is viewed as an individual's self-regulated actions without coercion from an external person or policy, and relatedness refers to an individual's sense of social connection with others. *Competence* is seen as an individual's sense of mastery in their profession. When these three core psychological needs are unmet, it can lead to reliance on external forms of motivation, lack of motivation or burnout (labelled as *Need Frustration* in SDT theory).

Understanding people's decision-making behaviour is especially important when the workplace requires complex and heuristic tasks coupled with deep information processing or creativity [10]. SDT suggests that proper feedback, autonomy, and control in decision-making can boost an individual's intrinsic motivation, engagement, and overall job performance [39]. Self-direction is a significant determinant of job satisfaction and motivation, as people need to feel competent and autonomous to be motivated [39]. Workplaces have the potential to either undermine or support these intrinsic propensities. In an environment where autonomous decision-making is supported, people excel and overcome challenges; however, when freedom is restricted, their motivation to perform decreases [39]. This is because autonomy fosters a sense of ownership and intrinsic motivation, which drives people to engage more deeply and persist in overcoming obstacles. Yet, when autonomy is restricted, motivation to perform decreases. Competence is supported by the provision of information that is not controlling, leaving the choice of how to respond to feedback [47].

Design practice and LA interpretation are not enacted in isolation but situated in the work context. There is a risk that the way technology providers set up educational systems could limit instructors' decision-making autonomy [52]. SDT emphasises that satisfying the needs for autonomy, competence, and relatedness is essential for maintaining intrinsic motivation and that intrinsic propensities can be facilitated or undermined by social conditions or technologies in the workplace [39]. In a recent study, LA dashboard development was guided by SDT showing positive results for improved LA usability [40]. In another SDT study [37], researchers found that within Australian higher education, teaching academics often experience their need for autonomy restricted. The interplay between the role of a teaching academic and the affordances provided by LA is important to understand.

The adoption of SDT as a lens for understanding improved workplace outcomes has led to several framework extensions. Most notably, Manganelli et al. [28] created a hypothesised framework based on a systematic literature review, highlighting how workplace practices can benefit by supporting SDT. The eight constructs of the framework, underpinned by SDT, include *Work practices*, *Need Satisfaction*, *Need Frustration, Autonomous Regulation, Controlled Regulation, Psychological, Behavioural,* and *Organisational Outcomes. Need Satisfaction* occurs when the need for autonomy, competence or relatedness is met. Conversely, *Need Frustration* arises when the need for autonomy, competence or relatedness is not met. The framework indicates how these constructs lead to different work outcomes, organised according to *Psychological, Behavioural,* and *Organisational* outcomes. This framework provides a lens to interrogate instructors' decision-making processes when challenged by data literacy, education design choices, and emotional responses when using LA to inform their design decisions. Our study adopts Manganelli et al.'s [28] SDT framework to understand how LA informs educational design processes and how the current LA systems can lead to more substantial alignment between LA and diverse educational design practices.

3 RESEARCH QUESTIONS

Our study aims to examine instructors' perceptions of LA and how it is used to inform their decision-making during course design through the following research questions: (1) How does LA inform instructors' course design decisions? (2) How can LA better support instructors' design decisions? The study employed SDT as a theoretical lens to understand instructors' decision-making when using LA to inform course design improvements. By offering a deeper understanding of instructor decision-making processes in LA contexts, our framework aims to guide future LA development and the implementation of more effective instructor support systems, leading to more positive instructor decision-making and psychological outcomes.

4 METHODOLOGY

A qualitative and interpretive approach was applied to address the research questions and unpack university instructors' perceptions of how LA informs their educational design and decision-making [11]. The research used a case study design to explore the instructors' current practices and aspirations for using LA to support learning design [29]. Aligned with the interpretivist paradigm, focus groups were selected as the data collection strategy to allow instructors to share their ideas collectively through in-depth discussions [20]. These conversations enabled participants to reflect on their experiences and find connections or deviations with other instructors' experiences [30]. Drawing on Layder's (1998) adaptive theory as a methodological framework, the data analysis integrates the principles of grounded theory with the application of SDT [22]. By utilising Layder's adaptive theory [22], the added strength of combining pre-existing theory to provide structure and coherence to research data while simultaneously allowing for adaptation based on patterns emerging from the data itself is possible. Institutional ethics approval was obtained before purposive sampling was used to identify university instructors employed within a single Academic Unit. This ensured that all participants' leadership and unit-wide policies and performance standards were consistent. Participants also had to have experience using or accessing the University's LA dashboards and reports.

The study comprised six focus groups involving 23 university instructors at a large public Australian university. All the study participants were teaching either in Education or Enabling Preparatory programs. Five study participants were also program directors who provided curriculum and teaching leadership to a specific program of study. The number of focus groups undertaken aligns with commonly used qualitative research practices, suggesting that theoretical saturation is reached between 4 and 6 focus groups [18]. For the purposes of the study, the participants are represented by a focus group (e.g. FG1), followed by the participant number (e.g. p1, p2). The focus groups were conducted through video conference technology and recorded for subsequent analysis.

The audio files were transcribed verbatim, and two coding cycles were done in Atlas.ti [54]. The analyses were done inductively, and the results were interpreted through the lens of SDT theory constructs. Inductive coding enabled the principal data analyst to analyse and crystalise the participants' lived experiences [30]. In the paradigm of a qualitative inductive approach, the focus is not on inter-rater reliability; the criteria depend on measures of credibility and dependability reflected in the trustworthiness of the analysis and the presentation of the results [17]. Data segmentation was done on a unit-of-meaning basis. The first data analysis cycle was conducted using in vivo coding, where participants' words are used as codes [41]. During the second cycle, these codes were grouped based on their similarity, thus forming themes. Coding was accompanied by written memos, enabling a deeper understanding of the data [41]. Data coding and the analysis were done co-currently, using the constant comparative technique [6]. By grouping similar codes together, in tandem with extensive memo writing, themes were developed. The themes and related codes were then interpreted through the lens of SDT by drawing on the affordances of Atlas.ti as a visual network [41].

5 FINDINGS AND DISCUSSION

Our results address the following research questions: (1) How does LA inform instructors' course design decisions? Themes 1-5 offer insights into instructors' current design and redesign practice LA development (2) How can LA better support instructors' design decisions? Themes 6-10 offer their visions for future LA development. Table 1 summarises the emergent themes, example quotes, and how they align with the SDT constructs.

From our results, we adapted Manganelli et al.'s framework [28] to better reflect the specific education context and role of LA as an enabler or impediment to instructor satisfaction and job performance. Our analysis led to the development of the *Data-informed Educational Design Decision-making* framework that included instructors' *Need Satisfactions* and *Need Frustrations. Need Frustration* refers to psychological needs that are in some way thwarted. In contrast, *Need Satisfaction* refers to psychological needs that are supported [28]. We collated the psychological *Need Frustration* and *Need Satisfaction* reported by participants in the various themes.

The proposed framework depicts an instructor's experiences as they make data-informed decisions. Although LA meets instructors' needs for competence by providing analytics on student engagement, it falls short in supporting their needs for relatedness and autonomy. This framework posits that instructors' experiences of *Need Satisfaction* can lead to positive educational outcomes, such as enhanced design efficacy and improved student engagement. Conversely, *Need Frustration* may result in negative outcomes, including diminished motivation and reduced instructional quality.

Table 1: Summary of themes and links to SDT

Theme	Example quote	SDT Construct	SDT Explanation
T1. Learning activity redesign based on student engagement data	*"one of the key intentions is understanding the patterns of engagement of my students."*	Competence	Design information obtained from the dashboard.
T2. Decisions based on assessment grades and data	*"What questions were they finding complicated"*	Competence	Design competence feedback obtained from assessment data and grades.
T3. Data-supported scaffolding design	*"I've used feedback practices and things like On-Task tool."*	Relatedness	Proving data that enables conversation or personalised feedback.
T4. Data as a starting place for further exploration	*"Having that human involvement to then check."*	Relatedness	Following up with students and having a conversation. Lack of integrated LA tools to support further exploration
T5. Influence of emotions on data-informed decision-making	"*nobody is watching the thing (video), well, what's the point.*"	Competence	The consequence of negative feedback obtained from the dashboard.
T6. Customisable dashboards	*"Our systems aren't designed to give me that."*	Autonomy	The need for autonomy in setting up data dashboards and visualisations was unmet.
T7. Lack of ongoing data literacy professional development	*"We've got a lot more data floating around, but we don't systematically teach in professional development."*	Competence	Lack of competence to utilise the full range of LA options available.
T8. Support needed for data interpretation	*"added to my actions as a teacher to include data analysis from the course."*	Competence	Instructors need better feedback scaffolding to support their data interpretation.
T9. Shared dashboards as a conversational tool	"*be able to have a conversation around (the data).*"	Relatedness	Lack of relatedness with students.
T10. Student personas for educational design decision-making	*"I need the thumbnail sketch of this data represents this kind of student."*	Competence	The need for appropriate design information.

Notably, while instructors' need for competence and relatedness was met in Themes 1-3 (Need Satisfaction), their need for competence, autonomy, and relatedness were often unmet in Themes 5-10 (Need Frustration), potentially leading to varied emotional outcomes based on individual regulation strategies as indicated in Theme 5.

Our contribution expands Manganelli et al.'s framework [28] in four key ways: (1) illustrating the interrelated constructs relevant to data-informed instructors' course design decisions; (2) demonstrating how the *Design Context* can support instructors' design choices by addressing their *Need Satisfaction* and *Need Frustration*; (3) highlighting the impact of emotion and emotional regulation on instructor decisions in *Affective Response And Emotional Regulation*; and (4) identifying the *Psychological Outcomes* and *Behavioural Outcomes* of these decisions. The analysis demonstrates how LA-informed design can either satisfy or frustrate instructors' psychological needs, emotional responses, and regulation and subsequently influence various outcomes, as illustrated in Figure 1.

Under the *Design Context* in our framework, there are two key constructs: *LA Dashboard Design* and the *University Context.* our study, participants reported using LA extensively, with the university relying on Moodle as its primary Learning Management System (LMS) for course delivery and communication, especially at the course level (T1). Educational design decisions, particularly at the activity level, were also informed by data from Panopto. This video platform provides insights into student engagement, such as viewing patterns of lecture content (T1). Additionally, participants had access to OnTask feedback automation tool [32] that enabled them to personalise feedback and tailor student communication based on their needs. The use of feedback automation was highlighted in Theme 3.

Similarly, our study highlighted the university support systems and job design as critical contextual elements. There is common ground about what educational design means for university teaching [14]; however, it is important to consider institutional differences when making educational design decisions [46]. Some participants had previously taken professional development workshops on using LA and reported that it supported their ability to make data-based educational design decisions. However, there was still a need for ongoing support and professional development (T8 and T9). In the workplace context, job design also influences motivational aspects [28]. Even though educational design benefits from data-informed decision-making, the time allocated for this process may not provide the necessary time needed to process data as part of that process (T8). Understanding the design context is foundational to understanding instructor inquiry [31]. Moreover, educational design is considered a university instructor's core function [46] [14], and we suggest that LA should be systematically integrated into design processes.

Within the Need Satisfaction construct, the primary elements emerging relate to Competence and Relatedness. Competence relates to the two themes: Learning Activity Redesign Based on

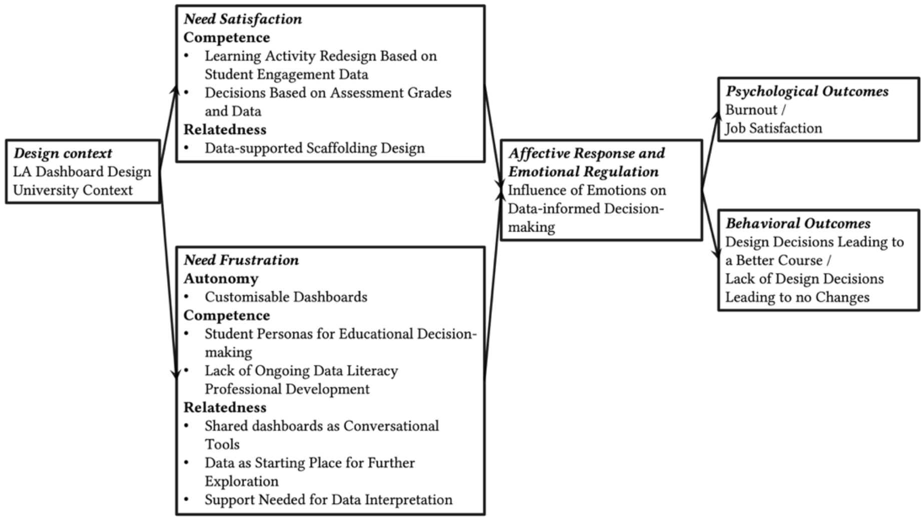

Figure 1: Data-informed Educational Design Decision-making Framework Indicating Instructors Need Satisfaction and Need Frustration adapted from Manganelli et al. [28]

Student Engagement data and Decisions Based on Assessment Grades and Data. The construct Relatedness links to the theme Data-supported Scaffolding Design. Regarding the first theme, Learning Activity Redesign Based on Student Engagement Data, participants shared that they would use LA to gauge what sections of the course students skipped over and where they struggled. For example, "I interpret that as a base level of engagement with this curriculum artefact or the set of artefacts. . .. to determine patterns where students seem not to be doing well" [FG3 p1]. Participants would review weekly engagement LA data to understand how the design works on the course level and fluctuations in student engagement. For example, "I'm constantly flipping between each week, points and clicks and engagement." [FG6 p3]. Participants' data-informed course design decisions differed. Generally, after three course iterations, participants were happy with the consistent engagement in their new course designs. When interpreted from an SDT perspective, the information obtained from the dashboard relating to their implemented design gave instructors suitable feedback that enabled them to improve their design practice [47]. Initially, instructors received negative feedback from LA; in other words, they realised that their design was not effective due to the lack of engagement from students in the learning activities. SDT indicates that even when negative feedback is given in the context of autonomy, the feedback can result in a positive outcome [39]. Most of the instructors in the current study were able to effectively act on the LA feedback and use that information to improve their design. According to SDT, competence feedback should not aim to control workers' actions; instead, it should provide dense and informational feedback that allows instructors to improve their competence.

Concerning the second theme, *Decisions Based on Assessment Grades and Data,* instructors in our study utilised assessment grades and assessment data, such as the time it took for students to complete assessment tasks, to guide epistemic task design, constructively align their learning activities and enable conversations with students. Participants used assessment grades and data to inform interventions. A participant noted using grades to constructively align the course with the assessment. For example: *"If they're failing a certain quiz at a certain time point, like, how can I build more activities like leading up to that to help support them into succeeding?"* [FG6 p3]. Our finding links well to Schumacher's [43] concept of "informative assessment" that underscores the distinct characteristics of data-informed approaches, extending beyond conventional formative and summative assessments. One participant pointed out that there are also limitations with using grades only: *"We've looked at, you know, aggregate test scores. But this spread is normally at a point where you can't really drill down on that because there's just this spectrum of students, some are going to do better, and some are just naturally going to do worse"* [FG2 p2]. A participant noted a similar problem identification strategy, where looking at the data-the time spent on questions during online quizzes -revealed the questions that students tended to struggle with, prompting them to consider revising the related resources and scaffolding, as one participant explained: *"What questions were they finding complicated and why and did that need to be covered differently in the curriculum"* [FG2 p3]. Overall, the participants used assessment data, grades or a combination of both to inform the course design better. The combined use of grades and data facilitated constructive alignment between the assessments and activities. Biggs [5] posits that the constructive alignment of learning outcomes, learning activities, and assessment is of the utmost importance in educational design to support student success. Having LA interventions with the key goal of assisting instructors and guiding them on better aligning their activities with the assessments could greatly benefit both instructors and students.

Within the Relatedness construct, *Data-supported Scaffolding Design* theme revealed that instructors' need for informational feedback was met when they actively engaged with LA, finding data-informed ways to provide better support and design better student pathways. The emphasis on targeted scaffolding, as discussed by Wise and Jung [50], was notably prevalent among the instructors in our research. We found scaffolding strategies were designed from the start of the course, and data was used to monitor how students used these scaffolds. By leveraging data-informed insights, participants were able to identify areas where students required scaffolding and provide targeted support, ultimately enhancing student learning and success. One participant's utilisation of data for scaffold design extended beyond her current course, incorporating data from other courses and adopting a preventative approach: *"Did they need to be scaffolded through? . . . Seeing if there's any previous data that I could use from other courses or similar courses that are designed in that way"* [FG1 p1]. Participants recognised the importance of scaffolding in mitigating student burnout by providing students with the necessary support and guidance to avoid feeling overwhelmed. For example: *"one of the triggers to burnout is someone who's logged on 50 times in a week."* [FG1 p5]. Set against a backdrop of information, the instructors could position the conversation in a way that helps students gain a deeper understanding of what students need to work on. Our findings extend that of Wise and Jung [50] by highlighting how instructors not only monitored students who exhibited signs of under-engagement but also paid close attention to those demonstrating over-engagement. This approach highlights the importance of recognising both ends of the engagement spectrum.

The relatedness between students and instructors emerged as a fundamental aspect of satisfying instructors' psychological needs. Using OnTask software, where sending messages to students who required additional support was possible, a targeted feedback mechanism allowed instructors to tailor their interventions based on data-informed insights, thereby fostering a more supportive learning environment. Aligning with the findings of Lim et al. [25], our study confirmed that instructors effectively utilised LA feedback within their course design. In online learning environments, fostering this relatedness can pose challenges; however, our findings indicate that instructors successfully navigated these complexities through a combination of educational technology tools and personalised check-ins with students. Providing scaffolded support and timely feedback is essential for promoting student well-being, and enhancing relatedness within the context of LA can further benefit instructors.

Within the construct of *Need Frustration*, the three key aspects of SDT identified in the study, Autonomy, Competence, and Relatedness, indicate the areas where additional support or LA development could assist instructors in their decision-making. Within Autonomy, one theme emerged from our study: Customisable Dashboards. Within Competence, the themes that emerged were Student Personas for Educational Decision-Making and the Lack of Ongoing Data Literacy Professional Development. Concerning Relatedness, the identified themes were Shared Dashboards as Conversational Tools, Data as a Starting Place for Further Exploration and Support Needed for Data Interpretation.

Our study identified instructors wanting the freedom to customise their data analytics to align with their educational design and to select visualisations that contain specific design feedback they need at a particular time (T6). This desire reflects a need for autonomy—the ability to control and personalise their data. Instructors knew what and when they needed data but could not customise what data they wanted to see. As one participant explained, he felt frustrated by his inability to have access to data related to when students view assessment tasks, *"I want them [students] looking at it [the assessment task] three weeks before they are due, so that's an important piece of data to me"* [FG6 p3]. Instructors wanted the ability to customise their dashboards. This *need frustration* is directly linked to the instructor's desire for complete control over the *physical design* [15]. This was because instructors wished to set up the data as part of the course design: *"What we want is context specific... what we want is to set up the data streams as a part of the design process"* [FG6 p3]. They also indicated that they would approach a course with a particular pedagogy or theory and would like to set up the data to reflect that.

Having visualisations akin to audio waves in audio-editing software was another idea by a participant: *"I wish it would give me a graph of their view counts going up and down across the length of my lecture [video]"* [FG6 p2]. Having a more fine-grained LA dashboard with a variety of visualisation options coupled with their designs to allow instructors to understand where they can improve their design would be helpful. The need for these visualisations differed from person to person. This need frustration could be explained by different levels of visualisation literacy, contributing to cognitive load [34]. According to SDT, autonomy is crucial for motivation and satisfaction [39]. However, autonomy *Need Frustration* is inhibiting instructors from optimal educational design decision-making. Having more specific data set up as part of the design process that is more detailed at specific critical points, which instructors indicated, would lower the cognitive load of having to work through unnecessary data. The ability to customise dashboards according to their particular interests and queries enhances their autonomy and empowers instructors to engage meaningfully with the data presented.

In the *Student Personas for Educational Design Decision-Making* theme (T10), participants envisioned designing with personas in mind. Participants indicated that they would expect two or three types of personas when they design a new course: *"And we started to develop personas for who were the students, what was the background positionality of students coming into our program without minimising and trying to generalise, come up with homogenous sort of personas"* [FG1 P5]. Participants suggested that having student profiles based on real-world data would make a tremendous difference. Student profiles would be data-informed representations of typical students enrolling in the course [3]. This type of student profile would ground their decision-making in data, as one participant explained: "*So, you've got participants in mind, and if we can get to the point where our data was linked, linking back, even just at the level of, you know, a factor analysis of some descriptive statistics to create the personas"* [FG3 p2]. Participants also considered AI an enabler in setting up the student profiles.

Student profiles would be data-informed representations of typical students enrolling in a course, helping instructors base their decisions on data, and could be generated using AI [4]. Even though student personas are not new, they have proved helpful to some instructors. Liley et al. [24] used personas in designing learning experiences to make implicit knowledge explicit, thus enhancing learning, especially in asynchronous contexts. Our study further highlighted that the instructors wanted more detailed information about their students to better support their design decisions. Zamecnic et al. [51] conducted a study where unsupervised machine learning models were used to create learner profiles based on demographics, digital trace data, and course performance, allowing for understanding learners in an online learning environment. By leveraging data and AI-powered learner profiles, instructors can gain valuable insights to inform their design decisions and create a more effective learning environment, ultimately benefiting learners. Having data-informed student personas would better support instructors' design competence, an important aspect of SDT, giving them information they can use when making educational design decisions.

The theme *Lack of Ongoing Data Literacy Professional Development* (T8) emphasised the importance of systematic professional development. The contrast between participants who have pursued professional development in LA and those who have yet to emphasise the importance of targeted training. One instructor said that the increased use of different platforms resulted in greater data availability but without systematic opportunities for professional development: "*We've got a lot more data floating around, but we don't systematically teach in professional development" [FG3 p1].* The participant who completed a professional certificate in digital teaching expressed a newfound proficiency in navigating LA dashboards and interpreting reports. This indicates that structured professional development can significantly enhance instructors' capabilities in utilising data-driven insights. Without suitable training, instructors may be overwhelmed by the data, leading to disengagement or misinterpreting critical information [35].

Since *competence* is a fundamental need within SDT, sustained and structured professional development could more effectively support the need to feel competent when interpreting learning analytics. In line with previous research data literacy was indicated as something that could be mediated by professional development and is similar to data literacy concerns [19]. Educational institutions must provide systematic professional development and ongoing support tailored to data analysis and educational design [19]. Such initiatives can help alleviate the cognitive load experienced by instructors, ensuring that instructors feel competent and supported in their role.

In the theme *Shared Dashboards as a Conversational Tool* (T9), participants suggested shared data dashboards to connect with students and for students to connect as a cohort. Participants in our study indicated that implementing shared instructor and student cohort-facing dashboards to facilitate communication could facilitate deeper conversations and dialogue with students and foster student collaboration and group regulation. Participants thought it would be a good idea to have student-facing dashboards that could be shared among students and between students and instructors. Moreover, instructors felt that the idea of students being able to see each other's progression might be a good way of starting conversations and acting as a catalyst for co-regulation: *"And the dashboard is a good way to do [that] and talking about the group thing is that those peaks and troughs, you know, you can look at that as a student and go AH... maybe I'm struggling because I'm doing this at 4 am. And the rest of the group are doing it at 7 pm"[FG4 p2].* Instructors also wanted the ability to log in as students and see what the students could see so their conversation could have a shared reference point, showing engagement data and activity patterns. The idea of using social comparison between students was investigated in a MOOC study, indicating that the availability of social comparison cues enhances course completion [8].

From an SDT perspective, having shared dashboards would increase relatedness between students and instructors. When teaching online cohorts, instructors noted that students no longer interact socially, missing opportunities to discuss class-related progress as a means of co-regulation. Instructors suggested that shared student-facing dashboards could help students monitor their learning and compare their progress with peers, potentially leading to discussions with peers or instructors about the reasons for differences. Co-regulation occurs when learners set their own goals or when a social environment influences their self-regulated learning through peer comparison [44]. Additionally, instructors wanted the ability to log in as students to see what they see, allowing for shared reference points in conversations and a better understanding of student engagement data and activity patterns. Participants indicated they missed conversations with student cohorts in online settings, similar to Salikhova et el. [42] research indicating a lack of relatedness in online settings. The lack of relatedness in online settings could be mediated by LA, which encourages co-regulated conversations by having the instructor and students share dashboards.

The theme *Data as a Starting Place for Further Exploration* (T4) highlights instructors' perception that LA data only reveals part of the story. For example, lack of student engagement may be due to various reasons, not limited to the learning design. Participants expressed a clear appreciation for the insights provided by LA dashboards; however, they were acutely aware that such data often lacks the depth required to fully understand student engagement and learning behaviours. This sentiment is encapsulated in the quote: *"It's data-informed, but it's not completely data-driven"* [FG1 p1]. The LA dashboard has limitations in informing design decisions. "*So the data does, you know, the numbers do tell us, give you some kind of trend, but they don't really give you the whole picture"* [FG6 p3]. To address these limitations, instructors designed their own surveys to supplement the dashboard data and obtain further information from students, emphasising the need for more nuanced information beyond descriptive statistics. Our research confirms that of Wise and Jung's [50], indicating that instructors who effectively use LA do not solely rely on data; instead, they also seek additional sources of feedback through surveys or directly asking students to better discern the causes of student behaviour. Effective use of LA data by instructors involves a dynamic process of inquiry, where data is just the beginning of a deeper exploration, ultimately leading to more informed and refined course design.

In Theme 8, *Support Needed for Data Interpretation*, participants raised concerns about the time and effort required to interpret LA data. Another common theme concerned the time and cognitive load required for interpreting LA data, indicating the need for support. Participants who flagged concerns about their workload felt that even though they could interpret the data, they needed more time to engage appropriately. Participants felt that data interpretation required considerable effort and a high cognitive load. Cognitive performance could be enhanced by better interface design [13]. Participants suggested that AI could make interpreting the data more accessible by presenting insights to the instructors. The participants thought this would encourage more instructors to use LA in their practice. As one participant commented: *"Here's the grunt work done. That would be a game changer for people's willingness and ability to use analytics"* [FG3 P1]. Participants suggested that AI could make interpreting LA data more manageable by presenting insights, possibly mitigating the need for high data literacy levels [27]. One instructor proposed the idea of 'smart dashboards' that could interpret data trends and provide insights into students' understanding, indicating this would encourage more instructors to use LA in their practice. Furthermore, instructors discussed the possibility of AI integrating data from different technological platforms, such as universities' learning management systems and video streaming platforms, to provide integrated analytical insights. Participants emphasised that the instructor should make the final design decisions, indicating the need for full autonomy in educational decision-making. Creating LA interventions that uphold SDT is a complex task; however, using SDT principles enables better uptake and motivation [48]. The strong need for support suggests that more scaffolding is needed for instructors to optimally use LA. From an SDT perspective, it is crucial that feedback is scaffolded so that instructors can manage and feel competent and grow, supporting their need for autonomy. Integrating the support of AI and professional learning in-situ could be a meaningful way of supporting instructors [21].

The *Affective Response and Emotional Regulation* approach associated with engaging with LA dashboards must be considered. As seen in the theme *Influence of Emotions on Data-informed Decision-making* (T5), instructors experienced various emotions, including surprise, disappointment, and joy. Zheng et al [53] highlighted that the instructor's experience level could influence the emotional response. Most participants in our study indicated it was emotional to see a lack of engagement from students: "*Most of the time, the data is a bit sad"* [FG1 p3]. Participants described their feelings when confronting low engagement data as *"sad"*, "*deflating"* and *"discouraging"*. Participants explained that they would typically spend a lot of time creating learning resources, only to realise that students skipped over them, making them feel they wasted their time. Another participant stated that she did not use the data for redesigning her course, saying that it was too discouraging: *"I don't think I really use the Panopto video data, in terms of course design thinking, mainly because it is just depressing to look at"* [FG6 p2]. When feeling discouraged by "bad" student data, there is a risk that instructors will avoid this negative emotion by avoiding LA feedback altogether (T5).

SDT suggests that there can still be positive results when negative feedback is given in the context of autonomy and choice [39]. Similar emotional responses were noted in previous research [50] [53]. The emotional response to data can either discourage or encourage future use of data in decision-making and is an important consideration in the support of instructors. Instructors reported that many emotions were experienced when confronted with digital data. Roth et al. [38] explain emotional avoidance as controlled emotional regulation, focusing on reducing emotions through avoidance.

Integrating better SDT-informed practices leads to better *Psychological Outcomes*. When basic psychological needs for autonomy, competence, and relatedness at work are not fulfilled, the detrimental effects of an extrinsic work value orientation on job outcomes become evident, leading to a decline in mental health [39]. We identified *Burnout* and *Job Satisfaction* as psychological outcomes. If an instructor does not see LA as part of their core role and the work as a data analyst is forced on an employee, it can hurt the instructor's mental health, leading to burnout. Instructors who reported being intrinsically motivated to explore dashboards found the role of data analyst satisfying, leading to *Job Satisfaction.* As noted by Kaliisa et al. [19], adopting LA is impossible if instructors cannot interpret LA dashboards. However, in our study, even instructors with high data literacy skills found the interpretation of the data too time-consuming. Participants reported that the time and cognitive load required to interpret data analysis was too much. Instructors now need to function as "data analysts" as part of their work duties, noting the risk of burnout (T8). Instructors saw the role of a data analyst as an additional burden, added to their already high workloads. As one participant explained: "*You have added to my actions as a teacher to include data analysis from the course. And that takes time. It takes time, it takes effort, it takes attention"* [FG3 P1]. Stress or burnout is often caused by instructors not protecting their time for teaching. Whitter [49] found that online teaching raises instructor stress levels due to a misalignment between workload and time allocation. A systematic literature review of the role of a university instructor made no mention of LA as part of an instructor role [46].

SDT predicts that *Behavioural Outcomes*, are more likely to be positive when SDT needs are supported [39]. As such, employees display more proactive, effective engagement in their tasks [28]. We identified two design-related behavioural outcomes that were influenced by the way instructors experienced these SDT constructs. Firstly, *Design Decisions Leading to a Better Course* and secondly, *Lack of Design Decisions Leading to No Changes.* Instructors would iteratively redesign, informed by LA, starting at the course level and working their way down to the activity level. The typical course redesign choices include 1) adding interactivity, 2) shortening or removing activities, 3) combining activities, for example, creating short videos followed by interactive elements, or 4) keeping the activities as is (T1). By implementing these design decisions, instructors could evaluate their design decisions and, in doing so, were able to close the data-to-design loop. After redesigning the course, the feeling of competence was rewarding to instructors as they witnessed an improvement in student engagement. Clow [7] described the learning analytics cycle as closed when the intervention is implemented with some effect on learners. On the contrary, instructors who could not get past the affective responses would disengage and avoid the problem, not making any data-informed design decisions (T1). When SDT needs are not met, this can result in a deeply emotional response and disengagement. Working through design problems requires a supportive environment that is intertwined with the contextual affordance available to instructors, as highlighted in our framework. Fully functioning requires Integrative Emotional Regulation, where instructors cope with negative emotional stress, considering the emotions themselves as an important source of information [38]. Recognising the affective response experienced by instructors in decision-making would help instructors recognise negative emotions, and learn to harness them as important decision-making information. Dealing with deep information processing coupled with the need for creative decision-making can benefit from SDT principles, highlighting the need for quality feedback, autonomy and control in decision-making.

6 IMPLICATIONS

The implications of these findings extend beyond individual instructors to higher education institutions and the design of LA dashboards. Higher education institutions and LA dashboard designers must recognise the importance of fostering a data-informed culture that prioritises the psychological needs of educators. This involves not only providing access to fit-for-purpose LA but also ensuring that instructors are adequately prepared and supported in their use of these tools. Addressing the *Need Frustration* experienced by instructors would lead to better psychological and behavioural outcomes. Professional development programmes should be designed to enhance instructors' data literacy, equipping them with the skills necessary to interpret and apply analytics effectively in their design practices. Fostering communities of practice where instructors can share experiences and insights related to LA will contribute to a culture of continuous improvement. Having LA formalised as part of the education design role would enable improved time allocation. It should also be noted that allocating time should be done in a non-controlling way, which could lead to diminished motivation. Having a formalised allocation of LA as part of educational design practice in instructors' job design could also enable corresponding formalised support. Addressing these gaps is crucial to enhancing instructor motivation and engagement with data-informed educational design.

7 LIMITATIONS AND CONCLUSION

The study was conducted in a single institution and within one academic unit. As a result, the findings and insights were likely influenced by the target institution's organisational culture and the type of LA and educational designs adopted. Future research will expand the analysis to encompass additional institutions and disciplines. Our study is the first to apply SDT to educational decision-making. Instructors' perceptions regarding LA and its impact on educational decision-making elucidate the significance of addressing instructors' psychological needs for competence, autonomy, and relatedness. To support instructors in their decision-making, there is a need to ensure they have access to reliable and insightful information. Furthermore, contextual elements highlighted in this study need to be considered. While universities can incorporate LA into their existing processes to complement student evaluations, it is essential that the goal is not to control or reward instructors based on this data, as doing so would undermine autonomy.

The emotional response to LA is a critical aspect to consider in higher education support services. Access to support staff with high data literacy and educational design skills could provide a much-needed interpretation of the LA data and its alignment with educational design decisions, thereby diminishing the emotional avoidance response. By enabling instructors to take control of their data setup, providing systematic support and professional development, and fostering social connections, educational institutions can create an environment conducive to effective data-informed decision-making. Ultimately, the goal should be to enhance the educational experience for both instructors and students, leveraging the potential of LA to inform meaningful improvements in courses and, consequently, improve student learning outcomes. The findings serve as a critical reminder of the need for a holistic approach to integrating LA into educational practice, one that recognises the intricate interplay between contextual elements, emotion, and pedagogical effectiveness. Our frameworks provide a way of understanding and supporting instructors in their data-informed decision-making actions, paving the way for future research, LA support, implementation planning and LA development.

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