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Effectiveness of a Learning Analytics Dashboard for Increasing Student Engagement Levels

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Abstract

Learning Analytics Dashboards (LADs) are gaining popularity as a platform for providing students with insights into their learning behaviour patterns in online environments. Existing LAD studies are mainly centred on displaying students' online behaviours with simplistic descriptive insights. Only a few studies have integrated predictive components, while none possess the ability to explain how the predictive models work and how they have arrived at specific conclusions for a given student. A further gap exists within existing LADs with respect to prescriptive analytics that generate data-driven feedback to students on how to adjust their learning behaviour. The LAD in this study attempts to address this gap and integrates a full spectrum of current analytics technologies for sense-making while anchoring them within theoretical educational frameworks. This study's LAD (SensEnablr) was evaluated for its effectiveness in impacting learning in a student cohort at a tertiary institution. Our findings demonstrate that student engagement with learning technologies and course resources increased significantly immediately following interactions with the dashboard. Meanwhile, results showed that the dashboard boosted the respondents' learning motivation levels and that the novel analytics insights drawn from predictive and prescriptive analytics were beneficial to their learning. This study, therefore, has implications for future research when investigating student outcomes and optimizing student learning using LAD technologies.

Notes for Practice

- Learning Analytics Dashboards (LADs) hold promise for enhancing the student learning environment by providing data-driven monitoring of students' learning progression and identifying overall learning trends and patterns.
- It is worthwhile integrating predictive analytics into LADs if transparency into how the models work and how they arrive at predictions for a given student is clarified.
- Data-driven suggestions offered by prescriptive analytics are appreciated by students and should be further researched and integrated into future LAD studies.
- Information-rich dashboards can incorporate multiple reference frames like the ability for students to compare themselves with their peers and monitor their levels of achievement toward their learning goals or progression with respect to their earlier selves without creating an overwhelming LAD that induces cognitive bias.

Keywords

Learning analytics, dashboard, descriptive analytics, predictive and prescriptive analytics, dashboard evaluation, student engagement behaviours, usability

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1. Introduction

Current advancements in technology-enabled learning have provided educators with new opportunities for enhancing student learning by leveraging Learning Analytics (LA). LA provides a research lens for uncovering student learning patterns from an ever-increasing amount of student data to better understand the overall learning process and to support students achieve their learning goals more effectively. LA Dashboards (LADs) are visual displays of information extracted from online learning environments that are arranged in such a way that student learning trends can be perceived at a glance (Schwendimann et al., 2016). LADs, therefore, hold much promise for enhancing the learning environment by providing data-driven monitoring of student learning progression so that actionable insights resulting in interventions can be taken to assist student learning.

Published LADs vary greatly in their complexity and sophistication of depicted insights. LADs based on descriptive analytics are the most common. They employ the simplest type of analytics that primarily depict current and historical data to identify trends. LADs that incorporate predictive analytics frequently leverage machine learning (ML) algorithms to provide forecasts about the likelihood of students achieving some predefined goal such as course or assessment completions (Shahiri & Husain, 2015; Rets et al., 2021). Meanwhile, prescriptive analytics capabilities produce data-driven feedback to students as well as remedial suggestions when necessary. LADs that incorporate prescriptive analytics are rare as this is the emerging frontier of current AI research (Susnjak, 2023).

The use of LADs is a relatively new adoption in education; it initially targeted educators to highlight students considered at risk of academic non-achievement. Purdue's Course Signals (Arnold & Pistilli, 2012) was one of the first widely deployed educator-facing dashboards that classified students into risk categories with respect to forecasted course outcomes. More recently, student-facing LADs have gained increasing interest in LA research (Teasley, 2017). LADs can facilitate more transparency into online learning behavioural patterns that can bring about new self-knowledge among students, enabling them to make more informed study-related decisions for improving their learning outcomes (Verbert et al., 2013). However, distilling large amounts of multidimensional data into relevant information that can then be converted into meaningful and actionable insights for students is challenging (Khosravi et al., 2021). These challenges relate to the requirement that the LAD is both informative and comprehensive. To be informative, the LAD should be easy to understand and effectively convey insights that are consequential and judiciously selected, not merely interesting. Whereas, to achieve comprehensiveness, a holistic overview of the student learning experience (Ali et al., 2013) needs to be depicted, combining data on learning content, learning activities, learning outcomes, and student abilities in an effective manner that does not result in cognitive overload. Finding the right balance between informative and comprehensive visual displays is not straightforward.

The effectiveness and proliferation of LADs in real-life use have also faced several challenges. Both educator- and student-facing LADs have increasingly incorporated predictive analytics to automatically identify at-risk students (Hu et al., 2014; Ahadi et al., 2015). However, this development has started to raise concerns centring on the prospect of widespread automated decision-making taking place with variable levels of human oversight (Hajian et al., 2016) while using machine learning (ML) models that are beyond obvious interpretation. Currently, published LADs that leverage predictive analytics do not provide users with any interpretation of their mechanics or any reasoning behind their predictions. Consequently, the development of accountable, transparent, and fair artificial intelligence (AI) technologies is being recognized as an important line of research in LA. Researchers in this field are interested in exposing the internals of black-box models to communicate the mechanics and provide explanations of the models' conclusions (Islam et al., 2022).

Additionally, while the sophistication and capabilities of the LADs have been increasing, the uptake and adoption of this tool have not matched the technological advances. It has been argued that one crucial factor determining whether students will use a LAD is their perception that the technology is predictable, reliable, and useful (Rienties et al., 2018). LAD research studies have posited that students will only engage with a LAD if they trust the data and understand how the predictions regarding them are formulated (de Quincey et al., 2019). Indeed, detailing the reasons why students receive a particular recommendation has been shown to increase their trust in the system and the likelihood of them following the advice (Bodily & Verbert, 2017). Although, when a model produces unexpected or erroneous output, trust is further eroded and could result in increased skepticism and possibly a rejection from the end user (Susnjak et al., 2022). These errors may have negative side effects as well, such as in instances when certain actions or decisions affecting others are taken, which might be based on false premises arising from misclassifications (Valle et al., 2021). While errors in predictions are not uncommon, they can to some degree be mitigated with explanatory technologies that unpack model behaviours. While crucially important, these kinds of explanatory capabilities are largely absent from present LAD implementations (Afzaal et al., 2021).

Lastly, a key challenge for LADs to improve their effectiveness has been in converting information into concrete and actionable steps for students. A central limitation of previous studies has been in developing prescriptive analytics capabilities embedded within LADs, which provide students with tailored suggestions on how to maximize their learning outcomes (Lepenioti et al., 2020). Increasingly new tools are now becoming available from the eXplainable AI field, which supports the next step in the evolution of LADs toward the incorporation of prescriptive capabilities that could embody the most potential for affecting improved learning outcomes of at-risk students.

This study seeks to contribute toward overcoming the above challenges and limitations of existing LADs by showcasing a student-facing LAD that integrates all levels of analytics as well as data-driven prescriptive analytics that offer tailored advice to students. Transparency of the underlying predictive model working is brought about through explanatory capabilities that offer detailed explanations of how the model has arrived at specific predictions for a given student. Additionally, these advanced analytics capabilities are combined with comprehensive visualizations. Studies suggest that student learning performance generally increases as their engagement level with the learning management system (LMS) also increases (Yu & Jo, 2014; Zacharis, 2015; Lu & Cutumisu, 2022). Therefore, this study aims to use measurements of engagement levels with LMS as a proxy of the overall learning performance. To that end, the goal of this article is to quantify the effect that this study's LAD has on student engagement levels with the LMS, and in parallel qualitatively analyze students' subjective perceptions of the dashboard's effect on their learning performances.

Schwendimann et al.'s (2016) review of LADs emphasizes the importance of grounding their designs in established educational theoretical frameworks. Jivet et al. (2018) note that only a few reviewed papers outlining LADs have taken account of theories within their design, while Verbert et al. (2020) call for more responsible LA designs with pedagogical underpinnings in the development of LADs. To that end, a key contribution of this paper is the rich grounding of LAD development within existing educational theory frameworks. Social comparison theory and self-regulated learning especially have informed the design and development of this study's LAD, SensEnablr, which enables learners through sense-making to take actionable steps. By situating this study's LAD within these pedagogical contexts and others, the study seeks to bridge the gap between LADs in general and educational theory in order to promote the use of this technology to enhance learning.

The study addresses the following research questions:

1. Does the SensEnablr analytical dashboard result in more student engagement with the learning materials within the institutional LMS?
2. What are the students' perceptions of the dashboard's effect on their learning performance?

2. Background

This section lays out the current state of research in LADs with an investigation into the different levels of analytics used by LADs in the literature. The literature review also considers the breadth of evaluations conducted on the effectiveness of published LADs.

2.1. Learning Analytics Dashboards

In recent years, LADs have rapidly evolved and have augmented simplistic descriptive capabilities by incorporating predictive analytics components. Hellings and Haelermans (2022) designed a dashboard aiming to provide study progress updates to students along with their predicted probability of success in a course accompanied by the predicted grade. Linear models were used to predict the grade, while AdaBoost predicted the course outcomes. A weekly email with the dashboard link was sent to participants with the intention of encouraging them to use the dashboard frequently. Dashboard usage was correlated with a positive impact on student online engagement, but no impact on final exam grades and course completions was detected. Similarly, Baneres et al. (2019) focused on devising an early warning system for students and educators that identified at-risk students. Their Graduate At-Risk (GAR) model used grades to predict course-level outcomes. GAR noted an improvement in the performances of the at-risk students; however, the effects could not reliably be attributed to the tool itself, or the interventions, as the primary factor.

In a separate study, Valle et al. (2021) developed a descriptive and predictive analytics dashboard. The descriptive dashboard displayed a student's performance relative to the class average while the predictive dashboard displayed the probability of the student attaining a specific grade. The authors reported that the predictive dashboard positively impacted only the highly motivated students to sustain their motivation levels, although both dashboards failed to demonstrate their effectiveness in affecting final outcomes. Recently, Duan et al. (2022) designed a LAD to provide students with actionable feedback on their weekly learning progress to advance their self-regulated learning skills and improve their course performance. A detailed inquiry using mixed methods was also conducted to study the dashboard's impacts on students. It was found that student use of the dashboard was positively correlated with their course performance, and those who viewed the dashboard had higher course ranks. In addition, the positive correlation associated with the use of the dashboard also extended to more timely homework submissions.

However, while such descriptive and predictive dashboards provide interesting and potentially revealing information, which is typical of most existing LADs, importantly they do not provide specific guidance and recommendations (such as guiding students toward relevant learning materials or activities that are likely to increase course performance) nor do they provide actual explanations of the predictions that may hold clues regarding possible remedial actions that students can take.

2.2. Predictive Model Explainability

Jayaprakash et al. (2014) argue that awareness of predictive model outputs alone does not influence course completion and retention rates unless these are combined with effective intervention strategies aimed at supporting at-risk students. However, it is also widely appreciated that predictive models have the potential to provide timely intervention for at-risk students that can result in them taking corrective measures (Namoun & Alshanqiti, 2021). Extracting maximal value from predictive models is the goal. Recent advances in machine learning technologies have shown how this can be achieved by not only enabling explanations of models and their predictions but also by generating data-driven and automated counterfactuals that can be converted into tailored prescriptive feedback. Ultimately, these outputs can articulate to the students what behavioural adjustments would hypothetically result in positive predictive outcomes. Such explanations hold potential in helping students regulate their online behaviour in a data-driven manner (Afzaal et al., 2021). Thus, arguably the most beneficial and insight-rich form of analytics is found in the prescriptive data-driven outputs that generate the greatest intelligence and value (Lepenioti, 2020).

As it currently stands, the focus of existing LADs (Baneres et al., 2019; Hellings & Haelermans, 2022; Valle et al., 2021) has been merely on conveying to students their at-risk status or probability of non-completion in a course. None of the existing predictive LADs adequately explain to users how the models work, or how their predictions were generated; rather, they merely provide the predicted outcomes as feedback to users. This compounds the challenges facing the acceptance and uptake of LAD technology since it has been noted that students would use these types of tools more frequently if they understood the outputs better and if they were provided with clear evidence that they are an effective tool (Kim et al., 2016).

Feedback is only effective if students can act on it (Ryan & Henderson, 2018). Several studies (Baneres et al., 2019; Kokoç & Altun, 2021; Li et al., 2019) have leveraged the dispatch of feedback in the form of manually generated messages and recommendations directly from educators. However, these examples of feedback were not individually tailored and did not specifically identify the learning strategies students ought to employ as a remedial response. Algorithmic approaches to automatically generate personalized, evidence-based, data-driven prescriptive feedback, therefore, hold great promise for improving outcomes.

2.3. LAD Impact

Examining the impact and perceived usefulness of LADs on student online behaviour, achievement, and skills is considered important (Bodily & Verbert, 2017) not least because these tools represent significant resource investments. But naturally also, because there is a need to quantify the effect of these tools to mitigate general worldwide trends in decreasing rates of learning performances and retention in tertiary education.

Few studies (Bañeres et al., 2020; Fleur et al., 2020; Kokoç & Altun, 2021) that focused on generating the student risk status to identify the at-risk students have claimed that usage of the LAD showed a positive impact on student outcomes for those who used the dashboards. Other studies (Bodily et al., 2018; Chatti et al., 2020; Han et al., 2021) have used qualitative approaches to evaluate general usability aspects like assessing users' perceptions of the tool based on their interactions. Bodily and Verbert (2017) conducted a review on a student-facing LAD and concluded that student use of LADs is generally not well studied nor adequately understood, and not having enough student evaluations "is detrimental to the research field of learning analytics because a lack of usability could be the reason why students do not like or use a system" (p. 417). The lack of student evaluations restricts us from knowing whether current LAD systems are adequately meeting the goals for which they have been designed. While recent studies like that of Duan et al. (2022) provided insights into the LAD's impact on course performance and homework submission time, more comprehensive evaluations would help researchers understand the full extent of the LAD's effect on self-regulation and learning strategies. Thorough student evaluations can therefore highlight end-users' perceptions regarding the LAD's usability, usefulness, and impact on self-regulating their learning strategies. Moreover, evaluations can help educators understand whether LAD recommendations are being properly communicated to students and whether those students feel motivated by the guidance offered.

3. Theoretical Framework

The design of the LAD in this study is supported and situated within various theoretical frameworks in education. Schwendimann et al. (2016) stressed the importance of anchoring LAD design in established educational theoretical frameworks. Their systematic literature review on LAD research identified key design features and explored the extent to which they were linked within these established frameworks. Their work found that very few LAD designs and implementations had articulated how their work was grounded. Overall, they identified six broad types of indicators related to learners, actions, content, context, result, and social, although how these indicators were linked to theory was not evident in the reviewed studies. Guiding LAD designs with educational frameworks, such as self-regulated learning (SRL), social comparison theory (SCT), and what could be termed as cognitive load theory (CLT), or feedback intervention theory (FIT) can demonstrate the benefits of learning and teaching. The review in this study shows that LADs grounded in SRL principles are more common, since these aim to provide learners with performance, progress, and strategy information to facilitate self-reflection and learning behaviour adjustments. A limited number of studies incorporated elements from SCT, displaying student data in relation to that of anonymized peer performance data to trigger greater motivation. Others still were designed with CLT principles, focusing on clear visualizations and actionable feedback to prevent information overload. Finally, a few studies referenced FIT, with dashboards providing real-time, personalized feedback to support learners in identifying areas of improvement and enhancing their performance.

The design of SensEnablr draws heavily from the SCT and SRL theories, but is also grounded within constructivism, SCT, and transformative learning (TL), which is outlined below. These theories help us understand how some of the more novel features of this study's LADs can be more rigorously justified and used effectively to enhance student self-awareness and self-regulated learning, and to raise academic achievement.

3.1. Social Comparison Theory (SCT)

The intention of LADs is to enhance student self-awareness, leading to improved self-regulated learning, and ultimately enhanced academic achievement (Lim et al., 2019). From a theoretical standpoint, for LADs to be effective, students require some form of "representative reference frame" for interpreting their data on a dashboard (Wise, 2014). The term "frame of reference" is an internal/external frame of reference (also known as the I/E model) proposed initially by Marsh (1986). The model proposes that academic self-conceptualization (or student perceptions of their own academic abilities) is shaped by internal and external comparisons. Internal comparison relates to measuring a student's achievements across dissimilar learning domains (i.e., different courses), while external comparison measures a student's achievement with that of their peers in the same learning domain. By using reference frames, students can build a self-concept or self-perception of their academic competence, as they gain awareness of their own strengths and weaknesses, which often leads them to refine their learning profiles (Skaalvik & Skaalvik, 2004). Academic self-concept is found to be highly related to achievement, interest, and aspirations, as increased perceptions of competency lead to increased levels of intrinsic motivation and vice versa, therefore, serving both as cause and effect (Marsh et al., 2005). Therefore, an effective communication strategy that mutually reinforces academic self-concept and academic achievement among students is crucial.

Current LADs too aim at increasing student motivation by presenting them with dimensional achievement comparisons that reflect both internal and external reference frames. Jivet et al. (2017) categorized student-facing LADs according to three types of reference frames: a) social (comparison with peers), b) achievement (distance toward goals), and c) progress (comparison with an earlier self). The social comparison can be made with the whole class, top students, and peers with similar goals. The achievement theory allows students to compare their performance level with desired goals from an internal perspective (i.e., set by themselves) or external perspective (i.e., set by their teacher). This frame might suit both performance goal-oriented students and mastery goal-oriented students because it makes it possible to focus on the learning outcomes and how they are mastering the materials and tasks. Progress allows learners to compare historical data of their performances with their current level of performance (Pintrich, 2000).

The first is expressed as an external frame of reference, while the second and third can be interpreted as internal frames of reference, but from a slightly different angle by using progression over time rather than as direct comparisons between various learning domains or courses. Social comparison is the most widely used reference frame for LADs as this can reveal learning behaviours among peers with similar goals and knowledge.

However, few studies have analyzed the effects of using external frames of reference in LADs on learning outcomes. Jivet et al. (2018) note mixed results in using comparisons with peers between low and high-performing students. For low-performing students, the social comparison frame was perceived as being stressful. In contrast, the high-performing students were motivated by seeing their success in comparison to others. Differences in the way students respond to frames of reference may be related to baseline motivation or self-perception of one's competency. In another study, Roberts et al. (2017) noted that while students favour using an external frame of reference that enables them to compare their progress with peers for self-evaluation, the way this information is presented needs to be carefully considered since for some students it could be detrimental.

3.2. Self-Regulated Learning (SLR) Framework

SRL is a theoretical framework that emphasizes the role of learners as active agents in managing and monitoring their learning processes (Zimmerman, 2000). SRL involves setting goals, planning, organizing, monitoring progress, and evaluating outcomes to optimize learning and performance (Pintrich, 2000). Within the context of LADs, the SRL framework can be a guiding principle in design and functionality to support learners in regulating their efforts. That is, LADs informed by SRL principles can typically provide learners with automated feedback about their performance, progress, and learning strategies, enabling them to reflect on their learning behaviours and adjust their approaches as needed (Howell et al., 2018). By offering actionable insights and fostering self-awareness, LADs grounded in SRL theory can empower learners to take greater control over their learning process, thus enhancing their motivation, engagement, and overall academic performance (Winne & Hadwin, 1998).

3.3. Further Theoretical Frameworks

Besides SCT and SRL, which heavily influenced the design of SensEnablr, other theories are also relevant. Constructivism posits that learners actively construct their own knowledge by building on their prior experiences and actively engaging with new information (Piaget, 1952; Vygotsky, 1980). Incorporating constructivist principles into LAD design involves providing students with meaningful and relevant information about their learning progress, which enables them to make sense of their performance, identify gaps in their understanding, and adjust their learning strategies accordingly. To achieve this, LADs can present data in a visually appealing and easy-to-understand manner, allowing learners to analyze their performance from multiple perspectives and recognize patterns in their learning behaviours. This process fosters self-reflection, critical thinking, and knowledge construction, which are essential elements of constructivist learning.

Moreover, LADs can be designed to promote social interaction and collaborative learning, aligning with Vygotsky's (1980) emphasis on the importance of social processes in knowledge construction. For example, dashboards can provide features that enable students to share their insights, experiences, and progress with their peers or engage in discussions about their learning. This exchange of ideas and experiences fosters a constructive learning environment, where learners can benefit from one another's perspectives and co-construct knowledge (Stahl et al., 2005).

In addition to individual and collaborative learning, LADs designed within the constructivist framework can also support the role of educators in facilitating the learning process. By providing teachers with insights into student performance, engagement, and learning strategies, LADs can help educators identify areas where learners need additional support, enabling them to intervene and provide guidance tailored to the specific needs of each student.

On the other hand, social cognitive theory (SCT) emphasizes the reciprocal relationship between personal factors, environmental influences, and behaviour (Bandura, 1986). According to this theory, self-efficacy, or belief in one's ability to achieve a goal, plays a critical role in motivation, learning, and achievement (Zimmerman, 2000). Firstly, LADs can foster self-efficacy by providing students with feedback on their performance, allowing them to monitor their progress, set realistic goals, and develop effective learning strategies (Zimmerman & Schunk, 2001). By presenting data on their accomplishments and areas for improvement, LADs can help learners gain a better understanding of their capabilities and adjust their efforts accordingly. This targeted feedback can enhance motivation, as students recognize their potential for success and become more confident in their ability to achieve their goals.

Moreover, LADs can incorporate social comparison features to promote vicarious learning, another key element of SCT. Vicarious learning occurs when students observe and learn from the successes and challenges of their peers (Bandura, 1986). LADs can display anonymized peer performance data, enabling learners to compare their progress and performance with that of their classmates. This comparative information can motivate students to improve, as they strive to achieve similar levels of success or avoid the pitfalls experienced by their peers.

Lastly, transformative learning (TL) theory posits that learners can experience a profound shift in their perspectives, values, and beliefs through critical self-reflection and dialogue (Mezirow, 1997). LADs can facilitate transformative learning by incorporating various features, including predictive and prescriptive analytics capabilities.

Predictive analytics within LADs enable learners to anticipate potential challenges and future performance based on their historical data and patterns. By identifying trends and uncovering potential obstacles, students can engage in critical self-reflection, reassess their learning strategies, and make proactive decisions to address potential issues. This process helps learners challenge their existing assumptions about their learning capabilities, fostering transformative learning experiences (Kitchenham, 2008).

Prescriptive analytics capabilities in LADs can provide students with personalized recommendations and actionable insights based on their performance data. These insights might include suggestions for improving study habits, prioritizing specific course content, or seeking additional support. By presenting these tailored recommendations, LADs with these capabilities empower learners to reflect on their current approaches and consider alternative strategies, potentially leading to a shift in their perspectives and beliefs about their learning (Cranton, 2006).

4. Dashboard Design

Considering the discussion of theoretical underpinnings connecting LADs with established theory, components of SensEnablr are presented here and linked to the reviewed frameworks.

The layout of SensEnablr can be seen in Figure 1, reflecting a comprehensive integration of both internal and external reference frames while the various components are anchored in the reviewed theoretical frameworks. The descriptive, predictive, and prescriptive components are structured into three columns. The first shows what is primarily a descriptive component that leverages the external frame of reference, drawing heavily from SCT to enable a comparison with peers, which prior works have found to be rarely used in LADs (Jivet et al., 2018). Meanwhile, the visualizations in this column also enable monitoring one's progress over time thus drawing on SRL as well. In this panel of visualizations, a student's engagement level is compared against the backdrop of their class's average. The engagement value is a combination of the number of login counts into Moodle, the number of learning resources accessed, and the total forum posts created, measuring communication exchanges with peers. By providing the learner with a reference point to their peers, the intention is to enhance student self-awareness with the goal of leading to improved self-regulated learning, drawing also from the SCT.

Figure 1. The SensEnablr LAD used for this study.

To highlight more clearly aspects of the charts in the first column, Figure 2, presents the weekly engagement scores of a specific student in comparison to the class average over the first seven weeks of the semester, illustrating the application of SCT principles. The engagement scores are derived from various indicators, including LMS login counts, forum discussion activities, and access to online learning materials, reflecting the student's level of interaction with the online learning environment. The student's engagement score consistently falls below the class average throughout the seven-week period, representing an external reference frame that the student can use for comparison. This trend suggests that the student may be less engaged with the course materials and online discussions compared to their peers. By leveraging SRL principles, the student can use this external reference frame to set re-adjusted goals, continue monitor their progress against the new goals, and continue to revise their learning strategies accordingly. Simultaneously, the student can employ an internal reference frame, focusing on their personal growth and improvement.

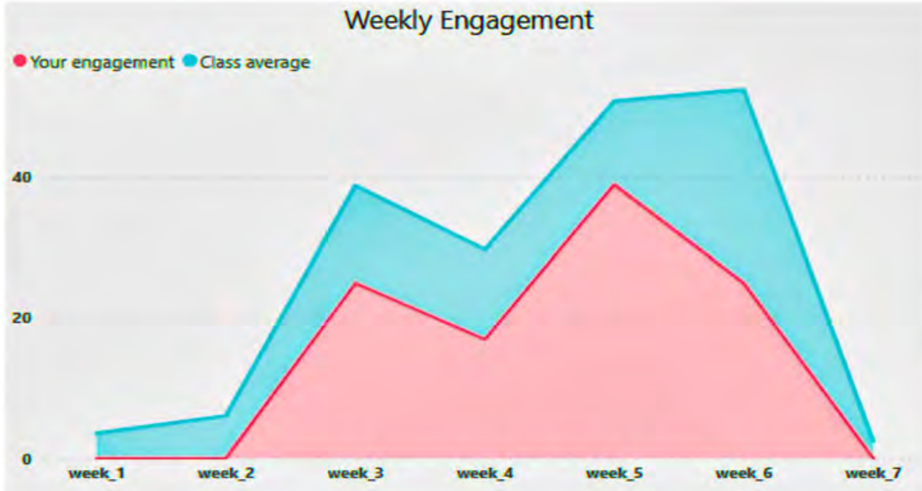

Figure 2. The enlarged chart of a student's engagement levels from the SensEnablr LAD.

The second column features both descriptive and predictive components. As with the first column, the descriptive components follow the external frame of reference, while also considering the principles of constructivism. It displays a snapshot of the student's assignment grades and test marks within the context of the whole class. Figure 3, for example, highlights one component from this section of SensEnablr where the student's marks across two assessments are contrasted with those of the class average showing a positive trend for the student.

The real-time feedback and information about their learning performance enables learners to actively construct their own understanding of the knowledge and skills they have attained and adjust their learning strategies as needed. In this manner, learners are empowered to use the dashboard to identify areas where they may need additional support or to track their progress toward their learning goals.

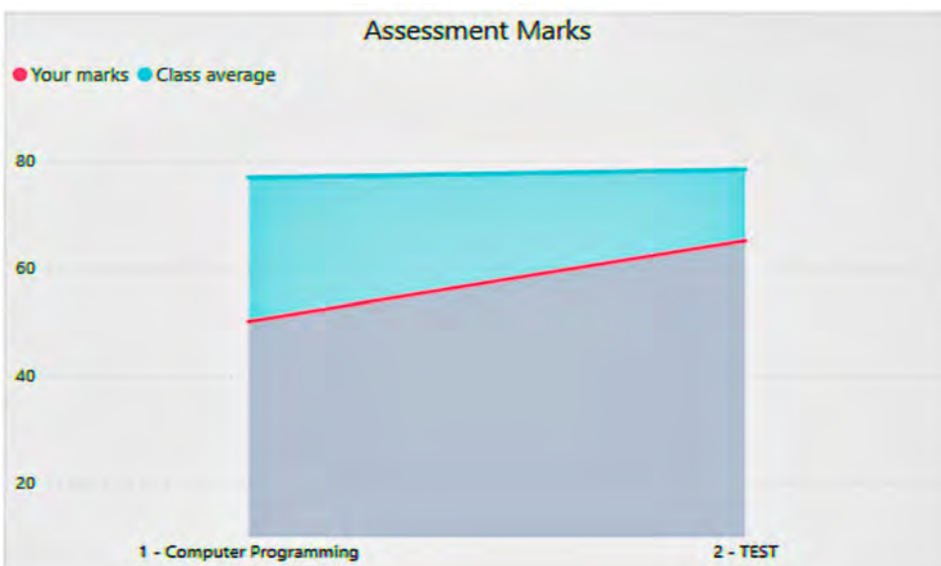

Figure 3. The enlarged chart depicting a student's assessment marks from the SensEnablr LAD.

The dashboard's predictive component begins in the bottom half of the second column. The student's approximate upcoming assessment scores are presented along with estimated scores for their final exam. These estimates are derived based on how students with similar learning attributes and performances from the same course in the previous year had performed, akin to a k-nearest neighbour approach.

The predictive component that begins here, draws from the principles of TLF where learners can critically reflect on their own learning progress and identify areas where they may need to challenge their assumptions and beliefs when confronted with a prognosticated outcome that they may not expect.

Finally, the key predictive and prescriptive components are seen in the third column, which continues both the application of the TLF as well as the internal reference frame (achievement theory). In this column, the student's overall course outcome prediction is displayed. In addition, the underlying model accuracy is communicated along with a simplified version of model interpretability to the one described in a subsequent section in Figure 5, highlighting only the top features and their relative strengths when formulating predictions.

Furthermore, in the last column, the dashboard contains model explainability that attempts to describe to the student how the model arrived at a given prediction for their case. The internal reference frame (distance toward goals) is reflected in the lower half of the third column where the above model transparency capability is further extended with the use of counterfactuals that provide the dashboard's prescriptive components. In this section, the dashboard offers recommendations to students on what modifications can be made to their learning behaviours for maximizing their learning outcomes. The automated feedback generated by counterfactuals offers data-driven personalized suggestions that can easily be configured to generate human-understandable text.

4.1. Dashboard Architectural Layers

In building the dashboard, the software artefact comprises three technological components, namely the data layer, the data analytics layer, and the presentation layer. The high-level architecture, with a description of the main tasks of each layer, can be seen in Figure 4. Meanwhile, there are two separate datasets (detailed in Sections 5 and 6) that were processed by this architecture and served different purposes. The first dataset (modelling) comprised past students whose data was used to develop the predictive and prescriptive models. The second dataset (dashboard) comprised students participating in the LAD trial, which also included data from their class peers in anonymized form.

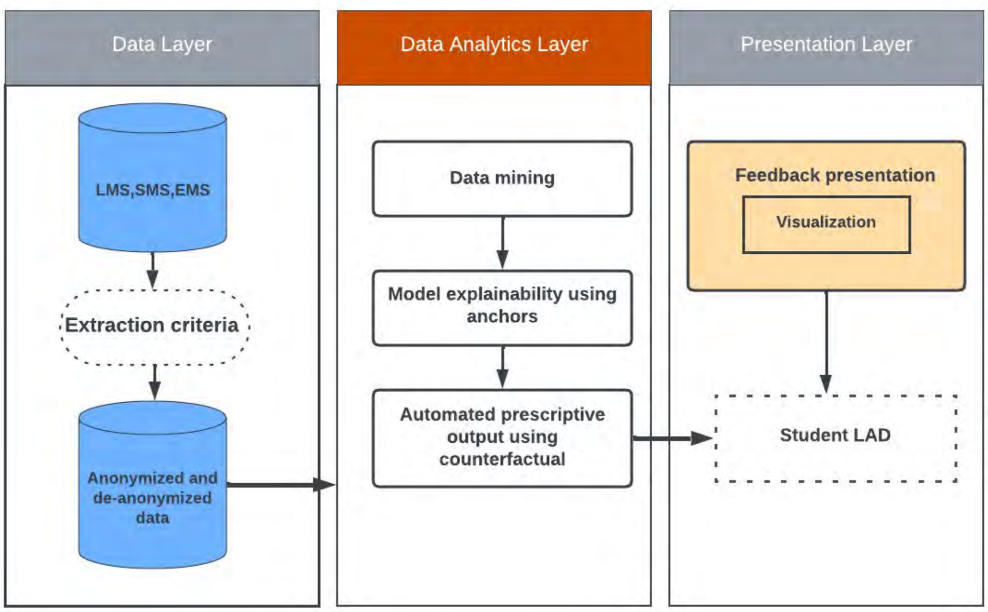

Figure 4. LAD implementation architecture.

In the first component, the data layer, the raw data comprising both the modelling and the dashboard datasets are extracted from several databases, LMS (Moodle), student management system (SMS), and the enrollment management system (EMS), and filtered based on target years and courses. The extracted modelling dataset is anonymized in its entirety, while the dashboard dataset is anonymized only to shield the identities of students who have not opted into this trial. The data is then cleaned and new features describing each student are engineered yielding a single dataset that can support the subsequent analytics tasks. The data extraction and processing step is conducted only once for the modelling dataset, while it is repeated on a weekly basis for the dashboard dataset to maintain an updated version of the LAD.

The data analytics layer consists of three tasks that support the accountability and transparency goals of predictive modelling as well as those of prescriptive analytics. First, the data mining step employs machine learning to build predictive models that identify students at risk of course non-completion by using the modelling dataset. This represents a one-off task that does not need to be repeated. The resulting models in this step are applied to the dashboard data for participating students to generate their predictions as well as the explainability outputs that described how and why the model has produced given outputs. Lastly, techniques that enable the automated construction of prescriptive feedback to the participating students are used.

The third component is the visual aspect of the dashboard where the aim was to integrate all the descriptive, predictive, and prescriptive components into a graphical representation. From a technical point of view, the visual aspect of SensEnablr was implemented following a client-server architecture using the Power BI web application tool (Knight et al., 2018) on the client side. The web application was populated with the data for each student and protected through authentication via logins. The dashboard was built on Power BI Desktop and subsequently deployed using the Power BI service on Microsoft's Azure cloud computing infrastructure. Meanwhile, Python's scikit-learn, and other libraries were used for building all the data layer processing and analytics tasks. More detailed explanations of these processes are discussed in the next section.

4.2. Dashboard Access

Only participating students who provided informed consent to opt into the study were given access to the dashboard that was advertised to a large body of students. The consenting students received the dashboard link via email, which allowed them to view their weekly performance. A manual guide explaining the login process and the usage of SensEnablr was also provided.

Students who did not consent to participate in the study did not have access to any parts of the LAD. To maintain privacy and confidentiality in compliance with the institutional ethics committee instructions, teachers and administrators were not granted access to the dashboard either. Only the research team that processed the data and developed SensEnablr, and the opted-in students could view the dashboard; furthermore, students could only see information specific to themselves. SensEnablr was made available to the participants four weeks into the semester and remained accessible until the end of the semester.

4.3. Dashboard Analytics

The nature of the predictive model used in the dashboard is outlined here. The focus is on describing the features (or variables) used for communicating the accuracy of the models achieved across several machine learning algorithms. The internal mechanics of the chosen model are exposed with respect to the impacts that the selected features have on the predictions and thus model interpretability is introduced. This section shows how this type of analysis is translated to the dashboard. It also discusses the technologies used to extract the explainability of the models to make the reasoning of the predictions transparent to students. Finally, methods used to embed prescriptive analytics aspects into the dashboard and the approach to automate this functionality are described.

4.3.1. Predictive Analytics

The training of the predictive models was conducted on anonymized data from the 4,000 historic students. New features were engineered to build the classification models. The aim was to engineer *course-agnostic* and thus generic features describing each student that were not tightly coupled to the particulars of different courses. Therefore, where possible the engineered features captured the relative values of a student compared to the mean values of their class. To achieve this, z-score (or standard score) was calculated on LMS data that relativized a student's score on a given feature with respect to those of their peers, capturing the degree of deviation from the class mean. In general, feature values for each student were calculated on a rolling mean basis where actions performed by students over multiple weeks were used as a single column, hence reducing the number of feature columns. This facilitated a reduction in the total number of features that helped mitigate the model overfitting problem. All the used features are outlined in Table 1.

Table 1. Feature Description

Feature name	Description
Average score of prior courses	The mean score achieved by a student across all previous courses, reflecting their academic performance history
Maximum score achieved in prior course	The highest score achieved by a student in any of their previous courses, indicating their peak academic performance
Prior course deviation score	The z-score of a student's prior course scores, representing how much their performance deviates from the class mean
Assignment score	The accumulated assignment scores received by a student in the current course
Assignment deviation score	The z-score of the student's mean assignment score, indicating how much their assignment performance deviates from the class mean
Prior role description	Student's primary activity during the previous year with respect to their current academic year (e.g., not employed, beneficiary, self-employed, wage or salaried worker, secondary school student, polytechnic student)

Table 1. Feature Description (continued)

Feature name	Description
LMS deviation score	The z-score of a student’s engagement score, expressing how much their engagement deviates from the class mean where engagement is calculated based on login counts, forum discussion activities, access of online learning materials
LMS engagement score	The total count of activities performed by a student on the Moodle platform, reflecting their level of interaction with the LMS based on login counts, forum discussion activities, access of online learning materials as a rolling 4-week average
Citizenship	Student’s nationality, which may influence their cultural and educational background
Age	Age of a student, potentially impacting their life experiences and learning habits
High school qualification	The highest school qualification a student obtained at admission, providing a baseline of their prior academic achievement
Study mode	Whether a student studies through distance/online learning or on-campus, which may affect their learning experience and engagement
Gender	Gender of the student, as it may play a role in their learning preferences and experiences
English proficiency test	Student’s English language proficiency level, as determined by standardized tests (e.g., IELTS, PTE, NZCEL Level 4, TOEFL), which may influence their ability to engage with course materials and communicate effectively

The predictive problem for the primary model was formulated to predict a given student as being either “high” or “low” risk category with respect to successfully completing their course. To achieve this, all the historic students in the dataset who gained 60% or less in their total course marks were labelled as high risk and the remainder as low risk. The models were then trained to map the features to the two outcome categories. Experiments were performed with a wide range of algorithms, namely CatBoost (Dorogush et al., 2018), random forest (Breiman, 2001), Naïve Bayes (Domingos & Pazzani, 1997), logistic regression (Hosmer & Lemeshow, 2000) and k-nearest neighbours (Hechenbichler & Schliep, 2004), from which the best performing algorithm was chosen for use in the dashboard.

A modified k-fold cross-validation approach was used to evaluate the models. The study’s dataset comprised seven different courses with a total of 10 separate deliveries across them. It was determined to train a model using nine course deliveries and to test each model against the remaining hold-out course offering. This process was repeated 10 times with different combinations of training and hold-out courses to arrive at final, aggregated evaluation scores. Measures used were total accuracy, the F-measure, and the Area Under the Curve (AUC) for comparisons. Table 2 lists the accuracies of all the models from best performing to the least accurate according to the F-measure scores, which are more reliable on datasets with imbalanced class labels since this approach balances the precision and recall values. Given that CatBoost achieved the highest scores, the models from this algorithm were selected to identify the at-risk students and to display its outputs on the dashboard. While comparing the accuracies of models across different studies is not always strictly valid, a recent systematic review (Namoun & Alshanqiti, 2021) has found that average accuracies currently range between 75% and 95%, thus validating that the generated models are within expected norms of reliability. The proposed prediction model developed using CatBoost was used to predict the future potential at-risk students.

Table 2. Performance Scores of Various Classifiers with Standard Deviations

Classifiers	F-measure	Accuracy %	AUC
CatBoost	.77±.02	78±2.1	.87±.02
k-nearest neighbours	.71±.02	71±2.4	.72±.02
Naïve Bayes	.68±.02	68±2.3	.71±.03
Logistic regression	.67±.03	68±3	.73±.03
Random forest	.67±.03	67±2.4	.74+.02

4.3.2. Model Interpretability

The behaviour of the model was validated by examining which features are most impactful and how their changing values influence the final prediction. For this purpose, the SHapely Additive exPlanations (SHAP) method (Lundberg, n.d.) is used, with its output depicted in Figure 5. A simplified version of this kind of output is presented to the students on the dashboard. In Figure 5, features are ranked and listed from the most impactful downward. The top four features are dominated by aspects

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of student performance in previous courses and their assignment scores in their current course, which testifies to the reasonableness of the model.

Within Figure 5, there is a secondary dimension that yields further insights regarding the model's mechanics corresponding to changing feature values. The *y*-axis colour gradient depicted on the right-hand side represents feature values, with green indicating high and red low values. The vertical line centring on zero on the x-axis represents the neutral effects of each feature on the final prediction. As the points for each feature extend to the right of the vertical line, the stronger the effects of that feature on predicting low risk for a given student becomes, and conversely in the left direction. Combining this with the colour gradient, it can be observed that as the average score of a student in their prior course increases, the higher the propensity for the model to predict a student as low risk, and likewise for the opposite scenario.

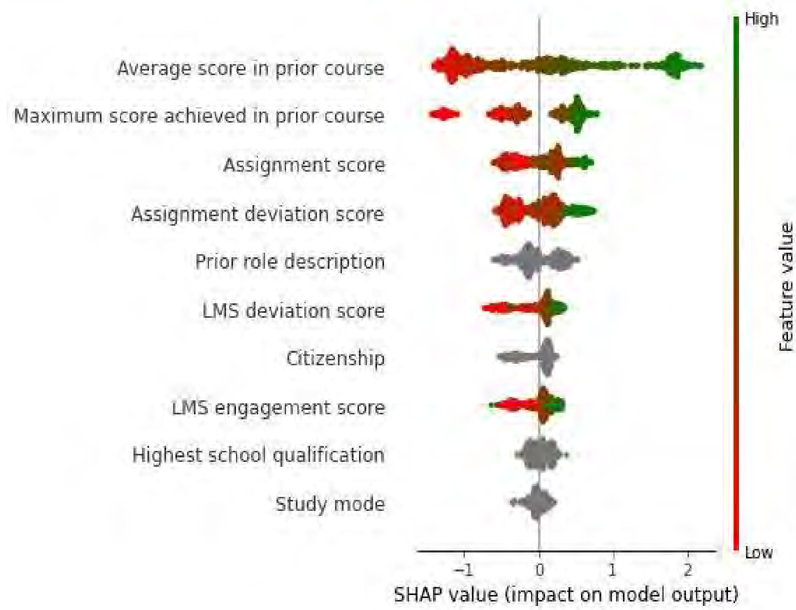

Figure 5. Feature importance plot with SHAP.

4.3.3. Model Explainability

While the high-level view of the behaviour of predictive models shown in Figure 5 is important, it does not have the ability to translate a prediction for a given student into the precise and clear explanation needed for the dashboard in this study. Though SHAP has the ability to explain individual predictions together with other technologies like LIME (Ribeiro et al., 2016), in this study it was decided to instead use Anchors (Ribeiro et al., 2018) that reduce a black-box prediction into a simplified rule-based description consisting of simple IF-ELSE statements. An example of this type of output is shown in Figure 1 with the presentation of the dashboard.

4.3.4. Prescriptive Analytics

Prescriptive analytics was implemented via the use of counterfactual modelling. This means that for a student identified as high risk, an alternative outcome was modelled for their scenario. Using their current input values and the trained predictive model, a minimal set of changes to the student's input values were modelled that would need to change for the predictive model to toggle its forecast to low risk. For this, counterfactual modelling was constrained to only the features that are actionable, thus ignoring immutable features like citizenship, et cetera. The outputs of the counterfactual modelling were then converted into textual output that takes the form of understandable feedback.

5. Methods

This section describes the dataset for training the models as well as the methods used for the recruitment of the study participants and subsequent evaluation of the SensEnablr dashboard.

5.1. Dataset

The dataset used for training both the predictive and prescriptive models in this study consisted of undergraduate and postgraduate students from an Australasian education provider between 2016 and 2019. As such, the data used for creating the models consisted of historic learners whose data was anonymized. The total size of the training dataset included 4,000 students across four years.

The student population in the dataset was diverse, covering three different disciplines: Business, Health, and Sciences. The gender distribution among the students was as follows: 65% female, 34% male, and 1% gender diverse. Additionally, the dataset included both full-time and part-time students, with approximately 54% of the students enrolled part-time and the remaining 46% full-time.

This comprehensive dataset provided a robust foundation for training the predictive and prescriptive models employed in SensEnablr. The diverse nature of the dataset allowed the models to capture a wide range of student behaviours and characteristics, thus contributing to the effectiveness and accuracy of SensEnablr's predictions and prescriptions.

5.2. Participants

Educational datasets used for building SensEnablr predictions followed institutional codes of conduct; hence an institutional-level research ethics protocol sets out boundaries on student data usage and limits authorized access to the available datasets. It further puts forth measures on maintaining learner privacy and preventing disclosure of past and current student data using de-identification methods (Mathrani et al., 2021). Accordingly, ethics approval was sought from the Human Research Ethics Committee at the host HE institution and subsequently approval to proceed was obtained both for building the prediction model using anonymized and aggregated student data and to further conduct research with those students who had consented to participate. Current students were informed about the nature and purpose of the proposed dashboard and invited to participate. Study participants comprised only those students who had voluntarily opted for access to the dashboard over the course of their study at the tertiary institution.

Approximately 500 students across five different courses (2 from Business, 3 from Sciences) were initially invited to participate in this study. Most participants were male (74%) and the remaining 26% were female. The study was advertised to students in-person during the deliveries of lectures as well as through LMS forum posts. Students were invited to email the research team if they wished to participate. In total, 30 student participants who had given their informed consent were given access to the dashboard, while other students could not access the dashboard. Moreover, to maintain student privacy and confidentiality, teachers too were not given access to the dashboard. Only the research team and the opted-in students could view the dashboard. Each participant was provided with the dashboard link through email to view their weekly performances. The participants were provided with a manual guide explaining the login process to access the dashboard. Nearly 59% of the participants were classified as "high-risk" in week 4 (i.e., before being given access to the dashboard). Meanwhile, by week 6 of the semester this fell to 39%.

All participants were familiar with the institutional LMS since they had earlier enrolled in courses that utilized the LMS. The said institution makes extensive use of Moodle (an open-source LMS) over which course resources (including digital book chapters, videos, and lecture recordings) are made available weekly to the students. In addition, discussion forum activities and learning tasks are designed for enabling students to jointly reflect upon the course content. Some courses made use of weekly quizzes that served as assessment activities. Student interactions with the LMS, such as their click-events as they access course resources were recorded automatically in the system's database, as were the number of logins to the learning dashboard.

Course duration typically lasts 16 weeks per semester. Four weeks following the commencement of the semester, dashboard access was enabled for participants and continued until the end of the semester. Over the semester, students were tasked with quizzes and assignments that were then graded and the marks allotted. Each student's final course marks are calculated from weighted averages of marks obtained in various quizzes and assignments as well as those from the final examination. While SensEnablr accessed and processed data from all students in a given course, only the opt-in students had access to SensEnablr, and they could only see information specific to them. Instructors also did not have access to SensEnablr.

5.3. Dashboard

Assessing the impact and usefulness of SensEnablr was a target for evaluation. Statistical approaches were used to evaluate the impact of the dashboard on student engagement with the LMS to answer the first research question. A paired sample t-test also known as a dependent sample t-test was performed to find whether significant differences existed between the two related variables (Zimmerman, 1997). In this study's case, the test compared the online behaviour of the participants with Moodle before and after using the dashboard. The purpose was to determine whether displaying the e-learning activities of the participants on the LAD had encouraged students to engage more with Moodle. Three different 15-day intervals were chosen for evaluation, each one designating the before and after conditions of using the dashboard. This analysis enabled us to make some inferences about the effects of the dashboard on short-term learning behavioural patterns.

5.4. Survey

In addition to an objective evaluation, a subjective evaluation of SensEnablr was also conducted. This involved assessing student perceptions of the dashboard's effect on their learning performance. Thirty survey responses were collected. The system usability scale (SUS) was used to evaluate the dashboard (Brooke, 1996), which is known to give a reliable measure of the perceived usability of a system even with a small sample (e.g., 8–12 users; Tullis & Stetson, 2004; Brooke, 2013). The participants were asked to provide Likert scale responses to the following statements:

1. I would like to continue to be able to use this dashboard for improving my performance.
2. The dashboard presents relevant information that users can easily understand at a glance.
3. The dashboard is user-friendly and intuitive to use.
4. Insights about my learning activities from the dashboard motivated me to continue learning.
5. The dashboard made me aware of my current online engagement behaviour and helped me improve.
6. The prediction of my risk-profile had a positive impact on my attitude toward my studies.
7. I understood the key drivers behind the predictions of my risk-profile.
8. The prediction reasoning on the dashboard was clear about how the prediction of my risk-profile was made.
9. The prediction reasoning was a useful insight.
10. In future, I would like to see suggestions about what I can modify in my learning patterns which might result in better learning outcomes.

Responses to these questions were formulated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The total score is 100 and the maximum point for each question is 10. For each odd-numbered question, 1 was subtracted from their score while for each even-numbered question, 5 was subtracted from their value. These were added up; finally, this total score was multiplied by 2.5 to ensure that the maximum is 10 for each of the questions (Tullis & Stetson, 2004; Brooke, 2013).

6. Study Analysis and Findings

This section presents results from the statistical and survey analyses that measure the effects that SensEnablr had on students. The analyses seek to investigate both the impact of its usage on participant behaviours after accessing the dashboard and its perceived effectiveness based on reported survey responses.

6.1. Dashboard Analysis

The purpose of this analysis was to determine whether any significant changes in student engagement levels with the LMS had occurred in a period immediately following interactions with the dashboard (which was defined as 15 days). The paired sample t-test was conducted on data covering three 15-day before-and-after sequences covering the full range of the teaching semester in order to compare the online behaviour effects of the participants after interacting with the dashboard.

The null hypothesis (H0): $\mu d = 0$, states that the difference in means between sample 1 (before using the dashboard) and sample 2 (after using the dashboard) is equal to 0. The alternate hypothesis (HA): $\mu d \neq 0$, states otherwise. The mean frequency of the participants engaging with Moodle was, on average, 115 times in the lead-up to the use of SensEnablr. This increased to an average of 213 times following the SensEnablr interactions. The t-test produced a statistical value of -2.14 with a p-value of .033. The p-value thus confirms that this constituted a significant difference of means at a .05 significance level, allowing us to conclude that the online engagement with Moodle was different before and after interacting with the dashboard. However, this effect was not long-lasting. When the t-test was conducted to determine if the increased engagement with the LMS continued for students for a further 15-day period after the initial interaction with SensEnablr, the results confirmed that the differences were not significant.

6.2. Survey Analysis

The participants were asked to respond to a survey questionnaire for evaluating the dashboard's usability and its perceived effectiveness when they were halfway through the course. The purpose of this evaluation was to investigate whether students consider the dashboard useful in guiding them in adjusting their learning behaviours and if it motivated them to improve their learning outcomes. The outcome of the survey results is shown in Figure 6. The overall evaluation of the SUS questionnaire resulted in an average score of 70.5 points. In general, a score above 68 is considered positive (Brooke, 1996); therefore, it can be interpreted that from the standpoint of the students, the dashboard was perceived to be helpful.

The survey responses corroborate the previous statistical results where a significant increase in engagement with the LMS was noted in response to interactions with the dashboard. The strongest and most positive response was registered on the question of whether or not SensEnablr motivated the students to continue learning. Sixty-seven percent responded as strongly agreeing with this assertion while a further 13% agreed with it. Therefore, an increase in engagement levels with the learning materials offered through the LMS can be assumed as a plausible effect arising from reported increases in motivation levels by the students' post-interaction with the LAD.

With respect to the predictive analytics features of the dashboard, 87% of respondents either agreed or strongly agreed that displaying their risk profile positively affected their attitude toward their studies, with the remainder disagreeing. However, while the same percentage of respondents thought positively of the explanatory aspects of the model's reasoning, some further work in refining the dashboard is needed since two-thirds of the respondents did not agree that the dashboard was sufficiently clear enough about what the exact drivers behind the predictions of their stated risk-profile were. Concerning the presentation of the prescriptive analytics features, 80% of the respondents were positive and indicated that they would like to see suggestions on which learning behaviours they should modify to improve learning outcomes. In considering the general issue of whether the SensEnablr satisfied the requirement of being both comprehensive and informative without inducing cognitive overload, two-thirds of the respondents either agreed or strongly agreed that users can easily understand the information at a glance.

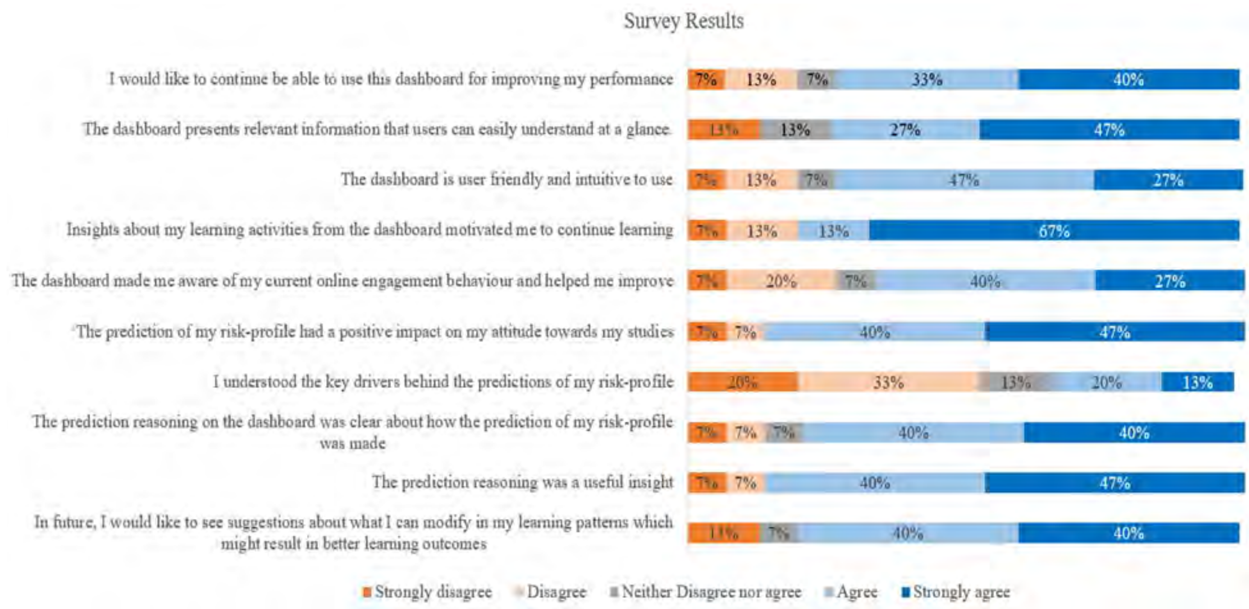

Figure 6. Survey results.

7. Findings

Despite the increased use of LADs by higher education institutions, we find that existing studies have not fully leveraged and integrated all available analytics capabilities. As such, no dashboard to date has brought together descriptive, predictive, and prescriptive components, highlighting this gap regarding maximally extracting value from analytics technologies. Beyond pure academic interest, this research grounds the novel machine learning features implemented in SensEnablr within the existing theoretical frameworks and justifies their inclusion and value for supporting and enhancing learners and their outcomes. The descriptive analytics components, while unsophisticated, motivate learners to evaluate themselves by comparing their LMS levels of engagement with that of their peers, thus drawing on social comparison theory. Meanwhile, the embedded ability for learners to monitor their progress over time both with LMS engagement and assignment scores enables a greater degree of self-regulated learning to take place. The constructivist principles also come into play within SensEnablr, since learners can make sense of their performance through the assessment score visualizations, from which they can identify gaps in their understanding, and be motivated to adjust their learning strategies accordingly. The decision to display to students where their assessment score performance is situated relative to their peers and what their next assessment score is likely to be (all things being equal), learners are empowered to set better and more realistic goals that support the development of greater self-efficacy, as outlined by social cognitive theory. Meanwhile, the predictive components that prognosticate a learner's possible course outcome have the potential to initiate within learners a profound shift in their perspectives and beliefs through a confronting and critical self-reflection that challenges their existing assumptions about their learning capabilities, as outlined by transformative learning. But, in assisting learners to subsequently formulate new strategies as needed, the prescriptive features in SensEnablr then also help learners develop new strategies with additional insights.

Finally, while there is theoretical support for developing and using LADs in real settings, there is limited research investigating the overall effects of LAD usage on students. This study contributes to addressing these gaps by investigating LAD effects on students. Thus, in response to the first research question, this study explored SensEnablr's effects on students through the prism of changes to engagement levels with the LMS. Our statistical analyses confirmed a significant improvement in the level of engagement with Moodle before and after using the student dashboard. The effect was observed over the short-term, with increased levels during the first 15 days following the use of SensEnablr.

The second research question measured student perceptions of the dashboard's effect on their learning. Generally, SensEnablr scored positively on overall perceptions of its effectiveness while scoring well on usability. Importantly, the survey results showed that two-thirds of respondents found the dashboard insights about their learning activities motivated them to continue learning, which aligned with the statistical analysis showing that students engaged with the LMS more after interacting with the dashboard. In our sample, students were highly in favour of being shown predictive outputs of their risk profiles and were equally desirous of being offered clear prescriptive feedback through the LADs. However, further work needs to be done on making the transparency and understandability of the models and their outputs more comprehensible.

Overall, the integration of multiple frames of reference as defined by Jivet et al. (2017), and the attempt to utilize more fully all types of available analytics capabilities, have demonstrated promise and grounds for further refinement of future LADs. By anchoring SensEnablr within the reviewed theoretical frameworks, this work provides a comprehensive approach that ensures student learning experiences are well-supported by established educational theories. Within the context of this experiment, it may be said that empowering the students with their own student-centred LAD plays a role in enhancing their awareness of their performance in comparison with that of their classmates; it can turn them into more responsible and competitive students who want to positively strive with their peers. Consequently, a student-centred analytical dashboard as presented in this study represents a possible blueprint and a step toward enhancing the state-of-the-art in learning analytics research.

In future work, the plan is to conduct a much larger rollout of the dashboard and to conduct analyses involving a significantly larger participant cohort. A particular emphasis in this subsequent work will be on quantifying the effects of the dashboard on learning outcomes in the form of course completion rates and grades, with a focus on the effects on at-risk students in particular. The aim is to also re-design aspects of the dashboard to make some explanatory components surrounding predictive and prescriptive capabilities more understandable, admitting that there is room for improvement.

Furthermore, as students observe their progress and engagement levels relative to other students, this may bring about psychological distress in the form of anxiety or discouragement if their expectations are not met. The dashboard may also bring some distress to high-risk students, i.e., those considered on the path to non-completion or failure to meet learning outcomes. These questions need further research. The intention is also to make a dashboard extension for instructors to provide detailed visuals on student performance to assist in evaluating their online learning behaviour. By monitoring the online learning of students through a dashboard, instructors can support their students to perform better, especially those considered at risk of not accomplishing their learning objectives.

8. Study Limitation

Several limitations exist within this research. The sample size is relatively low despite our best efforts to recruit more participants. This naturally affects the confidence with which definitive conclusions can be made. Due to this, the differences in impact between high-performing and low-performing students seen in prior research could not effectively be investigated. Since causality is difficult to establish, it is not possible to claim with certainty that the increase in engagement levels of students who interacted with SensEnablr is due to this factor alone. There could be other factors at play that relate to the courses and assessments or required LMS activities at different points in time during a semester, which could be confounding factors. However, a mitigating factor is the fact that the study included participants from several different courses, each with its unique rhythm and schedule, and the fact that the opt-in students tended to commence their use of SensEnablr at different points in time. These factors, therefore, help attenuate any potential bias arising from the specific rhythms of individual courses. In future studies, ideally, participants would be drawn from a single large class so that changes in engagement levels of opt-in students could then be compared with opt-out students. A further limitation of this study was that the opt-in student group was not large enough to randomly split into control and treatment groups, which would mitigate some aspects of selection bias.

9. Conclusion

In this paper, a student-facing learning analytics dashboard (SensEnablr) was presented together with an evaluation of its effectiveness to impact on learning for a group of students. The dashboard was developed to prompt self-reflection in order to trigger positive behavioural adjustments when necessary. A rich set of novel analytics insights were used and grounded within several educational theoretical frameworks. With this alignment, the dashboard's design enabled students to self-evaluate their progress across external (comparison with peers) and internal (comparison with their earlier performance and their goals) frames of reference. The dashboard incorporated a mixture of descriptive analytics displays, more sophisticated predictive outputs, and prescriptive analytics that offered students automated data-driven suggestions.

An analysis of the effectiveness of the dashboard was performed to investigate if interactions with the dashboard were associated with increased engagement levels with the institutional LMS. As well, an accompanying student survey gathered participant data. Results showed that students did indeed exhibit higher engagement levels with the institutional learning platform and course resources immediately following interactions with the dashboard. Additionally, survey respondents overwhelmingly indicated that the dashboard increased their learning motivation levels and that the sophisticated analytics insights were beneficial to their learning. Future work aims to expand both the size of the evaluation group as well as the length of the investigation in order to conduct a longitudinal study to shed more light on the effects of this tool on academic attainment performance, course completion, and qualification retention rates.

Statement on Ethics

Informed consent was obtained from all study participants. All collected data was treated confidentially. This research has been approved by the university ethics board (NOR 19/55).

Declaration of Conflicting Interest

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