Ethical concerns and suggested mitigation strategies related to student-facing learning analytics dashboards – a narrative literature review*

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Abstract

Student-facing learning analytics dashboards (LADs) enable students to access and view learning analytics (LA) data. While having access to LA data and the related recommendations offer benefits for the students, there are several ethical concerns involved. This narrative literature review describes the ethical concerns related to student-facing LADs and lists suggested mitigations to minimize the ethical risks. Five ethical concerns were identified: threat to privacy, lack of transparency and fairness, potential misuse of power relations, prediction side-effects, and restriction on autonomy. Mitigations to minimize ethical problems were related to providing students with transparent information about LA in a clear, comprehensible way, complying with ethical guidelines and regulations, and implementing tools in the LADs that make it possible to manage the data as well as personalize the output. As a result of the study, a model of ethical concerns in student-facing LADs as well as principal mitigation strategies for these concerns are proposed.

Keywords

learning analytics, dashboards, ethics, transparency

1. Introduction

These days we live in a data-intensive world, and while many would link data-intensive systems to contemporary digital technology, the field of education has been one that has been driven by data for centuries. Exams, in-class performance, assignments, and attendance have always been recorded and measured from an institutional as well as teacher's perspective. Recently however, this form of measurement has been developed increasingly more from the student's perspective, and specifically as a means of following progress and increasing control over one's own learning while enhancing collaboration between teachers and students [1, 2]. The term 'learning analytics' (LA) refers to using data analytic techniques and tools to understand and enhance learning and teaching [3]. Large, machine-readable data sets, generated in relation to e.g., resource usage and assessments, are processed to create predictions, provide targeted support, and personalize learning [3, 4, 5].

Student-facing LA reports data directly to students [4]. This can be done via dashboards, which often provide information in a graphically rich manner [6, 7]. LA offers shareholders of educational institutions with significant benefits, such as enhancing student motivation [4] via personalized learning, improved self-awareness, and learning interventions [8]. It has been argued that from the viewpoint of consequentialism higher education institutes cannot opt out of applying LA, as utilizing LA can offer significant benefits for all stakeholders [9]. Yet, applying LA raises several ethical concerns related to for instance privacy, the transparency in data usage, and the distribution of power and benefits [6] [9]. Some see LA as a virtue-ethical dilemma contradicting the value base of higher education [10].

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Learning analytics dashboards (LADs) are user interfaces that display analytical data textually and visually, to communicate both data collection and sense-making processes regarding the student's performance [11] [12]. These are considered important tools from a student's perspective, as they reflect the learning measurement processes that until now have been relatively hidden, while allowing students themselves to follow, and intervene, when necessary, in their own learning methodology, based on what the data shows [13]. However, this heightened awareness of data-centric processes also comes with drawbacks. For while LADs can be seen as tools for fairness, they also draw attention to matters such as ongoing data collection from numerous sources, inadequate power balance in data flow, and potential inequalities in data presentation and interpretation from individual learner perspectives (see e.g., [14] [15]).

There are several frameworks and guidelines to assist ethical implementation of LA (e.g., [9] [10] [16]). There is also a vast number of studies on how to design a student-facing LADs (e.g., [7], [17] [18] [19]). For example, Bennett and Folley [6] have generated design principles to support ethical adoption of learner dashboards. Yet, there is a small amount studies focusing on student perceptions regarding the matter [4], which raises ethical concerns [20]. This study combines the results of previous research and responds to the call for research from a student perspective. For this reason, we focus on studies examining student perspectives towards LADs, as other stakeholders such as teachers maintain a different positioning, both as collectors and users of student-generated learning data, in addition to being representatives of the institutions themselves. This assumes a distinct privileged power positioning, counter to that of the students who are subject to the systems.

The aim of this study is to ascertain ethical concerns of LADs based on student perceptions, while including suggested mitigation strategies related to these student-facing LADs. In this study, we analyze and describe phenomena [21] considered to be ethical concerns related to learning analytics. This study belongs to the field of social informatics, as it is described by Sawyer [22]. The study is problem-oriented as it focuses on ethical concerns of LA, and treats computing holistically as a composition of computers, software, rules, norms, and practices of people. It acknowledges the role of the context, in terms of fashioning meaning for the problem. In this case, the context is that of LA in educational institutions, and the ethical values and goals associated with these institutions. This study sees students as social actors who are affected by LA practices. The problem is viewed critically, and although this is not an empirical study, it serves as basis for further empirical study.

This paper is organized as follows. First, the concepts of LA and LADs are defined. After that, the research method is described, whereafter the ethical concerns related to student-facing LADs are discussed together with suggested mitigation strategies. Lastly, the results are discussed by drawing them together into a model of ethical concerns in student-facing LADs and the principal mitigation strategies related to these concerns are discussed.

2. Student-facing learning analytics dashboards

Student-facing LADs are tools to present LA data to students. According to Bodily and Verbert [4], the dashboards should help students understand their learning progress via feedback and should give recommendations on what to do based on that information. In this section, the concepts of LA and LADs are defined.

2.1. Learning analytics

An often-cited definition in relation to LA is provided by SoLAR [23], which states that LA is:

> "...the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs."

Nguyen et al. [3] add the characteristic of the application as also acting (e.g. adapting) based on the data, and propose the following LA definition:

> “The application of data analytic techniques and tools for the purposes of understanding and enhancing learning and teaching” (p. 62).

In LA, different kinds of raw data are collected, which are then processed and reported [3]. The data is often linked to individuals, as this is how individuals benefit from the data collection, i.e., data drives personalized learning and enables targeted support [10] [11]. In order to achieve the most added value from these types of systems, multiple data sources are typically combined [20].

The variety of data that can be useful for LA is unlimited [11]. Data can be e.g., the amount of resource use (i.e., platform logins), assessments, logs on social interaction and time spent with resources [4]. In addition, the data can be social, such as social media activity in Twitter or Facebook [10], biometric, such as measurements of heart rate or body temperature [24], and geolocational, such as the usage of campus facilities [11]. Data can also be manually input into the system [4].

As a result of data processing, LA applications provide information about learning activities, student engagement, student profiles and history [3]. This data can be used to predict future performance, to intervene when noticing students at risk, to recognize gaps in knowledge, and to personalize and adapt to learning styles [3] [11].

2.2. Learning analytics dashboards

A LAD can be described as a single display with multiple visualizations that combines learning related data [13]. Student-facing LADs provide real-time data to students about their progress and behaviors, usually in a visually rich manner [6] [8]. This means that attention is placed on the visual design and layout to ensure effective use of data visualization devices such as graphs and charts, as well as colors, icons and images. One of the earliest examples of LADs is Course Signals, which presented a red, yellow or green signal based on the calculated likelihood of succeeding on the course [25].

Bennett and Folley [6] categorize LADs into predictive dashboards, modelling dashboards, and descriptive dashboards. Predictive dashboards give predictions on outcomes, such as whether the student is at risk of failing or falling behind of learning goals. Modelling dashboards represent learning behaviors based on activities such as posting, commenting and time spent online. Descriptive dashboards display past learning behaviors, such as attendance, and score predictions for subjects.

LADs can be embedded in learning management systems (LMS), which are systems that support online or hybrid learning [24]. Data can be collected in addition to LMS from other systems, such as student information systems [24], integrated library systems [11], and third-party systems, such as the aforementioned social media platforms [10].

3. Method

The method in this study is that of a narrative literature review, which aims to describe the current state of knowledge in the area of inquiry [26] [27]. This study follows the six generic steps for a literature review, as described by Templier and Paré [27], and the best practices for a narrative literature review described by Green et al. [28]. First, the research problem was formulated and the conceptual basis for the review was examined.

Second, the literature search was conducted on March 15, 2025, targeting article titles, abstracts and keywords in Scopus and Web of Science, using the search term “learning analytic*” AND dashboard AND ethic*. The search resulted in 26 records in Scopus and 15 records in Web of Science. After removing duplicates, 28 records remained from the 41 records in total. At this phase, the corpus was also examined by the publication type, accepting only journal and conference articles, which led to the exclusion of six other records.

In the third step, the remaining 22 articles were screened for inclusion. The articles were screened based on title, abstract and in unsure cases also full text, including only articles that discuss student-facing LADs from a student perspective. Furthermore, the articles were also reviewed to detect whether they mentioned and discussed at least one ethical aspect related to LADs. At this stage, the articles were also reviewed by their type. Only empirical and conceptual-theoretical articles were included in the review. Four articles were identified as literature reviews and therefore were excluded from the corpus. After the screening, the size of the corpus was five articles. In addition, six articles retrieved via snowballing from the references (i.e., backward search) of selected articles were included in the review, totaling the size of the corpus in 11 articles.

In the fourth step, the quality of the articles was assessed through ascertaining that the papers were published after peer review. In the fifth step that focused on the data extraction, the 11 articles were read and re-read to identify the ethical concerns raised and possible related mitigations from each of the selected articles. Last, as the sixth and final step the identified concerns and mitigations were categorized into common themes. The reviewed articles and related themes are illustrated in appendix A.

4. Results

In this chapter, the ethical concerns related to student-facing LADs are described. Many of the concerns are not limited to LADs but apply to LA in general. It is also notable that these ethical concerns are highly context-specific and affected by the principles and values of the institution, student demographics, the policy environment, and the resources available to support students in interpreting and responding to analytics data [7]. The ethical concerns are categorized into five themes, which are the threat to privacy, lack of transparency and fairness, potential misuse of power relations, prediction side-effects, and restriction of autonomy.

4.1. Threat to privacy

The first theme, threat to privacy, refers to unauthorized or inappropriate access, collection, or sharing of students' data, violating their boundaries and policies. The threat to privacy arises from LA using sensitive and personal student data from multiple sources [24]. Several studies have revealed that students are cautious about protecting their privacy [17] [29] and concerned about possible abuse [17], and do not want to share data that they deem as being too personal, such as socio-demographic data, and data related to their activity in social media [17] [30]. These concerns for privacy may arise, for example via students being worried that other students are able to recognize them from the comparison data that the dashboard is showing to the students [31].

Mitigations: It is important to consider who has access to the data – students, institution, course instructor(s), third-parties – and what that access leads to [10]. Students should be informed regarding who has access to their data [11] and should have control over what data can be accessed, by whom, and for what purposes [19]. For example, in the LA system described by Divjak et al. [32], users could select whether they give permission to use all personal data, specific sets of personal data, or only anonymized data for different purposes. Also, the way that the system reports comparison data to students should guarantee anonymity [31].

4.2. Lack of transparency and fairness

The second theme, lack of transparency and fairness, refers to insufficient clarity about how data is collected, processed, and used in LADs. Jones [24] raises the concern that institutions do not clearly explain their information practices. Thus, both the benefits and threats of LA remain unknown to students. Students should be informed about the motivations of using LA and how the practices are in line with the norms, values and expectations of higher education [24] [33]. As mentioned earlier, students can provide data with their digital and physical movements and activities on a daily basis [20] [14]. Therefore, one often-asked question pertains to whether students are informed sufficiently about this ongoing data collection, in order to determine that they indeed have given their informed consent to data usage [20].

Mitigations: A key element here is transparency on every level of LA, regarding data collection, storing, processing and even the associated risks [20] [30] [33]. As a technical solution, privacy preference settings can be added to the student dashboards, where students would be informed about data collection and processing, and they could control what data is used [11] [24]. When providing information related to data usage and privacy, it is important to consider the format and timing of providing the information. Complex and lengthy privacy notices provided at an unsuitable moment may not be consulted by the students [33].

4.3. Potential misuse of power relations

The third theme, potential misuse of power relations, refers to the unequal power between students and teachers or people-in-charge, potentially leading to coercion or bias. According to Rubel and Jones [10], the position of power in LA is on the institution's side, and the benefits of LA are greater for the institution than for the students. It is the institution that determines the points of data collection, and obtains, stores and controls the use of data, including its disclosure, even to those from whom the data has been obtained. In addition, sometimes the institutional goals and student benefits do not align, which can lead to decisions that are not in favor of most students. Ifenthaler and Schumacher [30] also point out that the students´ willingness to share data to LAD systems is result of weighting the expected benefits to the risks. Thus, it´s important not to tempt students to share unnecessary data in the hope of benefits.

Mitigations: Students should not be forced to select between two unattractive choices, such as giving consent to data collection or opting-out of a certain course or functionality [11]. Also, one should be aware of situations where students might feel forced to give their data because of power relations, such as during the admission phase [24]. To be attentive to the student perspective, students, together with other stakeholders, should be actively engaged when implementing LADs [30].

4.4. Prediction side-effects

The fourth theme, prediction side-effects, refers to the inaccurate predictions that misrepresent student potential or reinforce inequities or injustices. As mentioned before, LADs may give recommendations and predictions for the students. It is important to acknowledge the possible bias in the data that these recommendations and predictions are based on. If students are profiled based on their first study year their identity might not be yet fully formed, nor their performance potential established [24]. Furthermore, students may misinterpret the data shown in the dashboards [32] and the predictions may cause unnecessary pressure due to constant awareness of progress [17], [29] [31].

Mitigations: Student-centered sense-making should be a high priority when designing a dashboard, so that students know how to interpret the predictive data [6] [32]. Students should also be able to control how and what predictive data they receive [19] [31].

4.5. Restriction on autonomy

The fifth and last theme, restriction on autonomy, refers to the threat of limiting students' ability to make independent choices by overly directing their learning paths. LADs might impose a risk of students changing their behavior either due to being conscious of monitoring, or due to internalizing values implicated by it (e.g., suggested career choices) [11]. Information may affect negatively how students experience their student identity or keep students committed to studies that they are not fitted to [29]. In the study by Klein et al. [19] students were worried that predictions could steer them and limit their academic exploration. While low-performing students may be put down by the information presented by the LAD, it might lead high-performing students to perform poorer if they outperform expectations [29]. Information provided by LADs may also give students the feeling that they are not being in control of their own education [29].

Mitigations: The dashboards should be customizable for students to maintain their sense of agency, and students should be provided with enough details to understand how the information is processed for them to decide themselves on their actions [6]. As a practical example on how to implement this, Ifenthaler and Schumacher [30] suggest offering easily accessible data in the dashboard (e.g., via clickable question mark icons) that informs about the algorithms and the raw data used, and about other factors affecting the presented data.

5. Discussion

In this paper, the ethical concerns related to student-facing LADs were categorized into five themes: threat to privacy, lack of transparency and fairness, potential misuse of power relations, prediction side-effects, and restriction of autonomy. Next, based on the results we propose a model describing the ethical concerns in student-facing LADs and suggest principal mitigation strategies. The mitigation strategies are formulated based on the literature review observations.

5.1. Model of ethical concerns in student-facing LADs

Drawing on the findings, we propose the model of ethical concerns in student-facing LADs. The model has five ethical domains that are represented in the form of five ethical concerns. Next, we discuss each of the ethical domains and propose principles to tackle ethical concerns. Finally, we present the model with mitigation strategies in Figure 1. First, threat to privacy belongs to the data handling domain and is one of the foundation ethical issues related to LA [34]. Although mitigations have been discussed to tackle this issue, we suggest that a comprehensive approach should meet the requirements that LADs need to implement robust data protection measures. These include anonymization (see [10]), encryption, and strict access controls. Measures should also include obtaining explicit, informed consent from students for data use. In addition, students should be provided with a genuine possibility to control access to their data [11].

Second, lack of transparency and fairness can be tackled by procedural justice in the sense that LADs should meet transparency and procedure fairness to ensure trust and accountability – also a key concern in LA deployment [35] [36]. The principal mitigation strategy is to provide clear, accessible explanations of data sources, algorithms, and dashboard outputs. Possible technical mitigations could be implemented to help students LADs also need to use visual aids or plain-language summaries to enhance student understanding. This is crucial from a legislative perspective as well, since the General Data Protection Regulation (GDPR) in Europe, launched in May, 2018, specifies that individuals must be supplied with unambiguous information about what data is collected, how it is stored and used, then they must make a decision based on this information before parties begin collecting personal data [37].

Third, potential misuse of power relations belongs to the power imbalance domain and is one of the ethical challenges [20] [38]. This issue is prevalent in the LADs system settings and is amplified by data-driven functions of the LADs system. It is important to view students as active agents who make choices and collaborate in the process of using LA, to minimize problems related to power relations [10]. The principal mitigation strategy is the establishment of ethical guidelines for LAD use to support rather than judge students. Also, students should be involved in co-designing the dashboards (see [30] [39]).

Fourth, prediction side-effects are related to predictive accuracy of the system. The cause of this issue is that predictive models in LADs can have unintended consequences if not carefully validated (see e.g., [40] [41]). Additionally, it is important to acknowledge that student identities can change, and thus data should be provided via a life span with an expiry date, and there should be the possibility to request data deletion [10]. This follows also the Right to Erasure as specified by the GDPR (see e.g., [42]). Also, always when making profiles based on data, there is the potential for discrimination and other problems that emerge from treating groups or segments in particular ways, based on demographics and prior academic success [10]. We suggest as the principal mitigation strategy validating predictive models with diverse datasets and methods to reduce bias and errors. Also, students should be able to control the data predictions, and the feedback should be designed to be both qualitative and quantitative in nature to minimize bias. For example, feedback from students can be planned, designed, implemented,

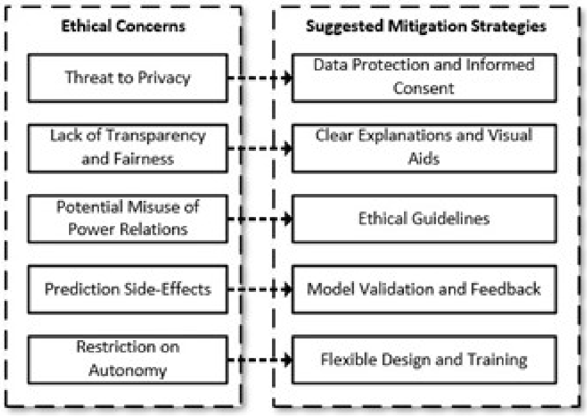

Figure 1: Ethical concerns and suggested mitigation strategies

and evaluated through a set of guidelines, using qualitative and/or quantitative approaches (see [43]). It can also follow recommendations based on students' skills to enhance their meta-cognitive strategies, such as persistence, knowledge awareness, and consistency, thereby improving the predictive accuracy of the system (see [8]). Furthermore, it is important to understand that student success is a complex phenomenon, and the data has limitations in its predictions [10]. Therefore, the chance of inaccuracies and false predictions should be communicated clearly to students and other stakeholders.

Fifth, restriction on autonomy reflects students' rights to self-determination, often challenged by prescriptive dashboards in the LADs systems [39]. We suggest that the principal mitigation strategy is to design LADs to offer recommendations rather than mandates, allowing students to opt-in or customize features. We also suggest that training should be provided on interpreting dashboard insights to empower decision-making. Figure 1 shows the ethical concerns and our principal mitigation strategies.

To conclude, the ethical concerns highlight the problematic situation if the student is not positioned as the active agent in the process of utilizing LA but instead forced to the vulnerable state of passive data source at the mercy of analytics (see e.g. [20]). Mitigation strategies aiming to minimize ethical problems stress the importance of providing students with transparent information about LA in a sensible way, complying with established practices of data protection and ethical guidelines, and implementing tools for the LADs that make it possible to manage the data as well as personalize the output.

5.2. Limitations and considerations

There are some limitations and considerations that should be taken into account related to the presented model of ethical concerns and mitigation strategies. The benefits and added value that LADs provide students should not be neglected, as they provide a source of information about their learning situation, currently and in the future [44] and offer the possibility for more personalized experiences [29]. Aspects highlighted as ethical challenges, such as showing student-level comparison data, can also strengthen student self-confidence [45]. Furthermore, there are studies where students have not raised concerns about control over their data (see [45]). In fact, Rets et al. [45] interpret the lack of concern regarding data control as being contingent on the clear ethical principles of their respective educational institute.

There are also issues that are rooted deeper than in the interaction with a single system in a single context and cannot be fully solved by a single solution. As an example, if the user has a habit of not reading privacy notices, merely providing easy access to the information will not offer solution [33], Furthermore, it should be noted that one mitigation strategy might generate another problem. For example, Roberts et al. [31] describe how adding personalization possibilities would support student agency but then foster possibilities for inequality between students as the other student may be provided with better learning opportunities. Lastly, we the authors of this paper acknowledge subjectivity induced limitation of confirmation bias in literature selection processes, due to our search being driven in a purposive manner.

5.3. Recommendations and future research directions

As an implication of our study, several recommendations and future research directions can be given. As is illustrated in the model, to succeed in open decision making and communication about LA, it is important that educational institutions have explicit ethical approaches [7]. It is also important to note that the usage of LA by academic staff is also affected by these ethical concerns from the student-perspective, as can be seen in e.g., Klein et al. [19]. The findings of this study suggests that future research focuses on how to make ethical guidelines and practices (institutional and LAD design) explicit and student-centered. While through our model we illustrate how communication and transparency is key to increasing transparency and leveling power imbalance, what we do not understand is how this information should be designed and communicated in ways that most students understand the benefits and risks of LA and how best to utilize the technology to gain educationally positive effects. To a great extent, the means of how educational institutions utilize LA remains invisible to students, and students may even be unaware of it altogether [36]. LAD is a mean to address this issue, as it visualizes LA to students, enabling them to use this information to their own advantage. Comparing the ethical concerns between LA in general and LAD is an interesting future research direction. To build basis for that research direction as well as other future research, as a next step we aim to utilize parts of our model as a theoretical background for an empirical study on student perspectives of the ethical concerns related to student-facing LADs.

6. Conclusions

This article focused on the ethical concerns related to student-facing LADs, while also reporting the suggested mitigation strategies for these concerns based on previous literature. As a result, a model of ethical concerns in student-facing LADs has been proposed. In this model, five ethical concerns and their respective mitigation strategies have been discussed. On the one hand, the ethical concerns relate to privacy and transparency of LA in general, yet on the other hand, they relate to the effects of the predictions – both accurate (student comparison) and inaccurate (lack of account for changing circumstances and sometimes poor data quality). The key mitigation strategies we propose are: raising awareness by providing information about LA in a sensible way, maintaining a high level of transparency through following carefully the existing ethical guidelines and established practices, and supporting student agency through enabling students to manage their data as well as personalize the dashboard.

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Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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A. Reviewed Articles

The Table 1 below illustrates which themes were discussed in which article. The themes are indicated with running numbers: threat to privacy (1); lack of transparency and fairness (2); potential misuse of power relations (3); prediction side-effects (4); and restriction on autonomy (5).

Table 1
Reviewed articles

Author(s)	Discussed themes
Roberts et al. [29]	4, 5
Ifenthaler & Schumacher [30]	1, 2, 3, 5
Rubel & Jones [10]	1, 2, 3, 5
Roberts et al. [31]	1, 4
Jones [24]	1, 2, 3, 4
Klein et al. [19]	1, 4, 5
Bennett & Folley [6]	4, 5
Droit & Rieger [17]	1, 4
West et al.[20]	2
Divjak et al. [32]	1, 4
Veljanova et al. [33]	2