A Review of Learning Analytics Dashboard Research in Higher Education: Implications for Justice, Equity, Diversity, and Inclusion

Kimberly Williamson
Cornell University
Ithaca, NY, USA
khw44@cornell.edu

Rene F. Kizilcec
Cornell University
Ithaca, NY, USA
kizilcec@cornell.edu

ABSTRACT

Learning analytics dashboards (LADs) are becoming more prevalent in higher education to help students, faculty, and staff make data-informed decisions. Despite extensive research on the design and implementation of LADs, few studies have investigated their relation to justice, equity, diversity, and inclusion (JEDI). Excluding these issues in LAD research limits the potential benefits of LADs generally and risks reinforcing long-standing inequities in education. We conducted a critical literature review, identifying 45 relevant papers to answer three research questions: how is LAD research improving JEDI, ii. how might it maintain or exacerbate inequitable outcomes, and iii. what opportunities exist in this space to improve JEDI in higher education. Using thematic analysis, we identified four common themes: (1) participant identities and researcher positionality, (2) surveillance concerns, (3) implicit pedagogies, and (4) software development resources. While we found very few studies directly addressing or mentioning JEDI concepts, we used these themes to explore ways researchers could consider JEDI in their studies. Our investigation highlights several opportunities to intentionally incorporate JEDI into LAD research by sharing software resources and conducting cross-border collaborations, better incorporating user needs, and centering considerations of justice in LAD efforts to improve historical inequities.

CCS CONCEPTS

• **Applied computing** → Learning management systems; **Education**; • **Human-centered computing** → **Visualization design and evaluation methods**.

KEYWORDS

Dashboards, Higher Education, Justice, Equity, Diversity, Inclusion, Literature Review

ACM Reference Format:
Kimberly Williamson and Rene F. Kizilcec. 2022. A Review of Learning Analytics Dashboard Research in Higher Education: Implications for Justice, Equity, Diversity, and Inclusion. In *LAK22: 12th International Learning Analytics and Knowledge Conference (LAK22), March 21–25, 2022, Online, USA.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3506860.3506900

LAK22, March 21–25, 2022, Online, USA

ACM ISBN 978-1-4503-9573-1/22/03...$15.00
https://doi.org/10.1145/3506860.3506900

1 INTRODUCTION

Learning analytics dashboards (LADs) are visualization systems that curate and present data about student learning and engagement in educational contexts [54]. They are increasingly used in higher education by a variety of stakeholders, including dashboards for students to monitor their progress in a classes [10], dashboards for faculty to monitor student learning and get feedback on their teaching practice [14], and dashboards for university administrators to manage and support students, instructors, and staff [22]. Although LADs are frequently used by faculty and students, many of them have been designed for staff engaged in student support services like academic advising [29]. In addition, most LADs are designed for scalability across many students, courses, and organizational units to facilitate their deployment at universities to reach growing numbers of students, instructors, and staff [2, 47]. In particular, providers of major learning management systems (LMS), such as Blackboard and Canvas, have added dashboards as a novel feature available to students and instructors [8, 33]. Given the pervasive use of LMS in colleges and universities around the world, including over 100 million Blackboard users [7] and over 30 million Canvas users [34] as of 2020, the dashboard feature in LMS likely exposed millions of students and instructors to LADs. The sudden widespread availability of LADs in academic environments raises critical questions about how LADs are designed and used, especially considering that many institutions are grappling with issues of diversity, equality, and inclusion.

Recent advances in learning analytics and educational data mining, combined with an increasing appetite for using data in decision making, have inspired significant research and development efforts around LADs [54]. Presenting insights from data collected by learning management and student information systems, LADs have been traditionally used to help students monitor their progress in a course and to help faculty monitor their course as a whole. The status quo of LADs is advancing quickly, incorporating new features like predictive analytics and guidance on how to make sense of the available data for those who make data-informed decisions like students and faculty. It is an opportune time to examine the state of LAD research, especially in light of recent calls to address social inequity in learning analytics [15, 56]. We conducted a critical literature review to understand how to improve justice, equity, diversity, and inclusion through LAD research and to highlight opportunities for future work in this area.

The acronym justice, equity, diversity, and inclusion (JEDI) has recently been proposed as a change from the commonly used terms diversity and inclusion (DI), or diversity, equity, and inclusion (DEI). This change is not just additive; it prioritizes justice and equity in efforts to address inequities. Truong and Martinez [60] discuss this shift with examples to explain the difference between the DEI and JEDI perspective: one example explains that DEI is "espousing that we value diversity and inclusion," while JEDI is "connecting these values to accountability for ensuring that our goals are met." In light of this shift, we opted to critically examine research on LADs from a JEDI perspective.

The learning analytics research community has identified a need for more critical scholarship about the work it produces [16, 55]. There are several systematic and comprehensive LAD literature reviews focusing on student usage [10], deployment of LAD applications [63], the use of learning theories in LADs [35, 46], and two general reviews of LAD research as a whole [54, 65]. However, no critical review of LAD research has been conducted thus far. While systematic literature reviews help readers gain a complete view of a field during a period of time, this broad scope is not conducive to highlighting critical issues in the literature [50]. Thus, because LAD research shapes the experiences of many people in education today, this shortcoming can have severe consequences for JEDI in higher education.

The year 2020 brought about a significant push to develop initiatives addressing issues of JEDI across all kinds of institutions and research communities, including Learning Analytics [15, 56]. Nevertheless, there is significant uncertainty about which directions will create meaningful change. Throughout this review, we will examine how issues of JEDI can be addressed in LAD research to help reduce systemic inequities that give rise to socio-demographic achievement gaps and the underrepresentation of historically disadvantaged groups. We aim not only to review the LAD literature for these challenges but also to highlight areas in dashboard research where researchers are in a strong position to address issues of social inequity. This critical literature review will add depth to the LAD literature by addressing the following research questions:

RQ1. How is learning analytics dashboard research being used to improve JEDI in higher education?

RQ2. How are inequitable outcomes unknowingly maintained or exacerbated in learning analytics dashboard research?

RQ3. What are the opportunities to improve JEDI in learning analytics dashboard research?

2 LITERATURE SEARCH

Following Paré and colleague's [50] definition of a critical review, we sought to "reveal weaknesses, contradictions, controversies, or inconsistencies" (p. 189) and "to highlight problems, discrepancies or areas in which the existing knowledge about a topic is untrustworthy" (p. 189). Unlike systematic and comprehensive reviews, a critical review uses a sample of papers instead of reviewing all literature in an area. We approached this review from a critical constructionist epistemology, wherein we searched for alternative ways of knowing and expose unrepresentative assumptions that have been embedded into knowledge [38].

Given that we set out to understand how LADs were being used in higher education to improve student learning outcomes, we initially chose the following inclusion criteria for articles in our review: papers about dashboards (a) with a student component (includes both student and non-student facing LADs) that are (b) used in higher education (within and outside of the classroom) and (c) used empirical research methods. We next determined the following search keywords by brainstorming keywords related to LADs: education dashboard, learning dashboard, learning analytics dashboard, advising dashboard, student dashboard, and higher education dashboard. We then compared the first few abstracts obtained from a Google Scholar search for each brainstormed keyword. We found that "higher education dashboard" returned the most relevant papers that met our inclusion criteria. We therefore chose "higher education dashboard" as the initial keyword and used Google Scholar and Scopus to record the metadata (title, journal, year, etc.) for the first 20 papers returned by the search to make the papers retrievable for later reading. These 20 papers were merely a starting point to discover relevant papers. One by one, we read the abstracts and sorted the papers into three folders: Criteria Match, Literature Review, and No Criteria Match. Papers matching the inclusion criteria were sorted into the Criteria Match folder. Existing Literature reviews of LADs were placed into the Literature Review folder. All remaining papers were assigned to the No Criteria Match folder. Figure 1 provides a visual description of the process we used to arrive at the final set of articles. The literature search was not limited to a specific time frame.

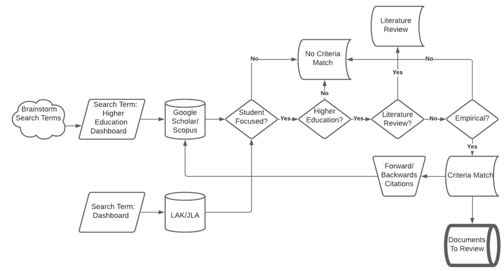

Figure 1: Flowchart describing the process used to collect articles for the this critical review sample.

We skimmed each Criteria Match paper, taking notes on the purpose of the study and how the paper did or did not address JEDI issues. We also performed a backward citation search by keeping a running list of papers cited in the review papers, which appeared to be potential matches for our inclusion criteria. The existing literature reviews were skimmed for a backward citation search also. Using the new list of papers, we recorded the citations of the papers and sorted them into the appropriate folders. To ensure that we did not miss closely related papers, we conducted a forward citation search on the papers in the Literature Review and Criteria Match folders. This forward citation search was conducted by searching Google Scholar with the paper's title and reviewing the "Cited by" papers. Unlike the previous steps where each paper was returned and sorted, we read the abstracts of each potential new paper and only kept the papers that were a criteria match.

As a final step in building our sample of papers, we searched for the keyword "dashboard" in the conference proceedings of *Learning*

Analytics and Knowledge and all issues of the *Journal of Learning Analytics*. These two publication venues were chosen for this final pass because they publish LAD research and represent our targeted audience. We broadened the search term from "higher education dashboard" to "dashboard", because the results returned were small enough to allow us to examine each paper that was returned. After all searches had been completed, The final list of publications was comprised of the initial 20 articles found by searching google scholar and scopus with the keyword higher education dashboard, and 15 articles from LAK and JLA with the keyword dashboard. Removing duplicates, applying our three inclusion criteria, and conducting a forward and backward citation search we arrived at 45 relevant articles and 4 literature reviews (27 articles were excluded). Table 1 displays the publication outlets for the papers included in this review (full list of papers on OSF: https://osf.io/tg5bn/).

3 THEMATIC ANALYSIS AND FINDINGS

We conducted a thematic analysis over the final sample of 45 relevant papers. To create our themes, we skimmed the papers again and reviewed the notes we had taken for each to develop an initial idea of the overarching themes. At this stage, we developed three broad themes regarding methods, dashboard usage, and software development. We then thoroughly reviewed each paper taking detailed notes on how it relates to the broad themes above. We accomplished this by using a template, where each theme was listed along with room to give an overall summary of how a paper relates to the theme with accompanying quotations. Although we searched for each theme in every paper, not all papers contained information on all themes. Therefore, the themes were continuously modified, redefined, and split out into additional themes during this process to accommodate the evidence provided by the papers.

Four themes emerged from the thematic analysis: Participant Identities and Researcher Positionality, Surveillance Concerns, Implicit Pedagogies, and Software Development Resources. In the following sections, each will be defined, summarized based on the evidence from papers in our sample, and related to the broader issue of incorporating JEDI into LAD research. We additionally summarize the themes and note related challenges and opportunities in Table 2.

3.1 Participant Identities and Researcher Positionality

JEDI-informed research needs to understand who was involved in the research (both researchers and participants) and how the inclusion or exclusion of people is reflected in the study findings and general implications. Even when a study does not have a JEDI focus, reporting simple statistics about the population can advance a collective understanding in the field about which groups might not be represented in the research. The socio-technical nature of dashboard research means that different methodologies can generate complementary insights. For this theme, we chose to organize the sampled studies base on their methodological approach to explore how identity information is presented.

We observe a strong methodological skew towards surveys and interviews in LAD research, which has also been noted in prior LAD research [46, 64]. We found many of the sampled studies applied multiple methods, with some studies using both qualitative and quantitative methods [1, 5, 9, 12, 14, 23, 28, 48, 68]. These studies mostly reported demographics related to sex, male/female percentages or numbers. Three of the studies that reported sex, only reported a number for females, thus suggesting that sex is binary, and the rest were male. In studies that relied on participants with expert knowledge, age and/or experience were also reported. One of the studies did report a percentage of "under-represented minority groups," but it was unclear what identities were included in this group. While most of these studies addressed inter-rater reliability for the coding of the qualitative portions of the study, none of them reported information about the coders themselves to determine if they were similar or dissimilar to each other and to the participants.

Other studies employed interviews or focus groups where a dashboard was presented to people to elicit their opinions and suggestions [19, 31, 39, 44, 53, 58, 67–69]. Like the previous studies, these studies mainly reported participant sex. However, all studies in this group reported numbers for all sexes instead of just one number and assuming a binary distinction. More frequently than sex, participants' experience and age were reported. In the case of studies focused on teachers, teaching experience was reported. In the case of student-focused studies, year in school or age was reported. These differences may be attributed to the smaller number of participants in interviews and focus groups.

In other studies, the researchers were able to observe how participants interacted with the dashboards in the wild by analyzing log data from the dashboard [11, 13, 20, 37]. It was not surprising that most of these studies did not include any participant demographic information since log data tend to have limited user information. One study did present socio-economic status in their dataset and reported results based on this indicator. Another study conducted at a "women's university" stated that their sample was therefore "100% female." This conflation of sex and gender leading to, incorrectly interchanging sex for gender, was present in almost all papers in the sample.

Although major funding agencies like the Institute of Education Sciences (IES), the research arm of the US Department of Education, is prioritizing randomized controlled experiments to answer education policy questions, such as "what works, what doesn't,"[32, 57], only five studies in our sample used an experimental design. Two of those studies were conducted in a live course where a random sample of students was granted access to a dashboard [3, 27] and reported the general information about the course, but not demographic information about the students. Another two studies conducted a within-subjects experiment in a live course with students granted access to a dashboard in some but not other weeks [4, 24]; and one experimental lab study in which participants evaluated four different dashboard conditions [45]. The former study reported just the sex of the participants, while the latter reported both sex and age. Controlled experiments are an essential methodological tool to demonstrate the effectiveness of dashboards that have been deployed into university environments. At the same time, the studies included in this sample provided little information about the study participants, and none of them provided a demographic breakdown by experimental condition.

Table 1: Number of the articles considered in the literature review by publication venue.

Publication Venue	Num. of Articles	Publication Venue	Num. of Articles
International Conference on Learning Analytics & Knowledge	6	Educational Technology and Society	1
Computers & Education	5	Higher Education	1
Assessment & Evaluation in Higher Education	3	Innovations in Education and Teaching International	1
CHI Conference on Human Factors in Computing Systems	3	International Conference on Information and Communication Technology (ICoICT)	1
Journal of Learning Analytics	3	International Conference on Learning and Collaboration Technologies	1
British Journal of Educational Technology	2	International Journal of Emerging Technologies in Learning (iJET)	1
Computers in Human Behavior	2	Journal of Computing in Higher Education	1
IEEE Transactions on Learning Technologies	2	Journal of Educational Technology Systems	1
Learning @ Scale	2	Journal of Research in Innovative Teaching & Learning	1
Technology, Knowledge and Learning	2	Teaching in Higher Education	1
Asia Pacific Education Review	1	The International Journal of Information and Learning Technology	1
Behaviour & Information Technology	1	The Internet and Higher Education	1
BMC Medical Education	1		

Table 2: Four core themes identified in this critical literature review. Each theme is summarized by providing a description along with challenges and opportunities for justice, equity, diversity, and inclusion.

Theme	Description	Challenges	Opportunities
Participant Identities and Researcher Positionality	The disclosure of participant and research identities in studies.	Protecting participants' privacy while also including enough demographic information so that context can be better determined to create policies based on research.	LAD researchers should collect and report demographic information from participants. LAD researchers should also reflect on their identities and experiences and how they influence their research studies.
Surveillance Concerns	Conflation of dashboard research with larger learning analytics privacy and surveillance issues.	Decisions about data access and visualizations are made by LAD researchers, and these decisions have consequences for how users make meaning of the dashboards.	Researchers should be transparent about all decisions made in the research, including ones they consider to be implied. Explaining these decision will give researchers an opportunity to interrogate the choices they make that could have negative impacts.
Implicit Pedagogies	The need for incorporating pedagogy into LAD research.	LADs have been created with the goal of supporting learning and instruction in a scalable way, but they are designed with certain values and user pedagogies in mind. This can neglect pedagogies that fall outside of the dominant narrative.	LAD researchers can design dashboards to be accessible to different pedagogies by making the dashboards more customizable, and use outcome measures that reflect the varying goals of instructors or advisors.
Software Development Resources	The development of LADs for research is a resource-intensive process where a large share of the development happens just a few countries.	The financial resources and software development expertise required to develop and deploy LADs, as well as the need for close relationships with institutional IT offices, make LAD research inaccessible to many researchers.	Making dashboard software open-source can significantly reduce the upfront costs of creating a LAD for research and foster research collaboration across institutions and borders, which can expand the reach of LAD research to more global contexts.

As research results have been used to justify and advocate for policy changes, this exclusion could exacerbate societal issues for minoritized groups who are not sufficiently represented in the research. Interviews and focus groups have been shown to amplify the voices of minoritized participants more effectively than quantitative methods, but there is a risk that smaller samples omit voices from marginalized groups [21]. This issue is exacerbated when a colorblind approach is taken to data analysis by not accounting for or addressing participants' demographics in the study. This lack of data implies a narrative that all participants are the same and reinforces the norms associated with those most privileged in a context [18]. As a field, the inclusion of demographic data can help other researchers understand which communities or contexts must be investigated to understand the boundaries of theories and frameworks, and to prevent potentially harmful policies from being deployed in contexts that the research evidence would not support.

In addition to missing participant demographic information, we did not find researchers positioning themselves within the research. By positioning, we mean reflections from the researcher about how their experiences and identities may impact their research from study design to the interpretation of results [49]. Nevertheless, it was encouraging to see numerous studies, typically qualitative studies, explicitly state their epistemology in the study context, and we hope this continues across methodological disciplines.

3.2 Surveillance Concerns

The large amount of data that LADs use to generate visualizations has sparked critical conversations about privacy and ethics of learning analytics and educational data mining. Regardless of whether research studies have an ethics or privacy goal, consideration of the ethical implications of their studies is important. This theme is grounded in the privacy and ethical concerns brought up by study participants. In our sample, there were six studies where privacy and ethical concerns were brought up by participants even though these concerns were not being studied [14, 26, 31, 53, 58, 67]. Although issues of surveillance were not central to these studies, it was the first time some of the participants became aware that their institutions were mining their data. While the data collection and mining was happening independently from and probably well before the intended research, participants still linked the potential of surveillance and lack of privacy to the research project.

In some studies, participants were cautious of how the display of the data could impact individual privacy. Participants in Roberts and colleagues' study [53], who were students at the university, were concerned that dashboard comparison features with other students could reduce their own privacy. Participants wanted the comparison features, but also wanted anonymity, which was possible for this particular research. In other studies, the research prompted ethical questions such as should students have the ability to completely remove themselves from the collection or display, instead of remaining anonymous [26]? This dilemma is currently being addressed at numerous institutions, weighing the risk of individual privacy with the learning benefits that can only be gleaned by full participation in the data. Some of the instructor-focused studies reported that faculty were also worried about their students' privacy [31, 58, 67]. These faculty noted that many students were unaware of the data mechanisms of the university and that information should be provided to students about data collection [58]. Other studies took this idea a step further, acknowledging the power relationship between instructors and students and suggesting that data could make this relationship more oppositional if instructors used the dashboard data as facts or surveillance against presumed future student behavior [24, 67].

Although privacy concerns were not the main focus of the dashboard studies, since in most settings they were using existing data infrastructure, these concerns came up in student interviews and focus groups. Not only were there concerns about student privacy, but there were also concerns from faculty about surveillance of their courses using data displayed in the dashboards. Brown [14] found that faculty were seeing the data collection as "unwelcome surveillance" of their teaching practices. They felt it was unclear who had access to the data and what decisions were being made with them. In one extreme example, a faculty member decided to remove all LMS data from their course dashboard, which limited the amount of course insights that the dashboard was designed to provide. Other faculty members, just like the students, expressed that their data used in predictive modeling should be anonymized. A remarkable feature of many of Brown's [14] observations was that most of the concerns extended beyond the dashboard. For example, a faculty member can prevent LMS data from showing up in their dashboard, but the university still has access to that data for modeling and data-informed decision making. While faculty and students expressed privacy concerns, the same concerns did not arise in advisor-focused studies. This could have been because early educational data mining research focused on early alert systems that were created to help advisors reach at-risk students. Thus, many advisors were already aware of the data collection and analysis that are happening at their institutions. Dashboards are sometimes students, faculty, and staff's first encounter with the large data systems at their institution, even though the dashboards merely display the data and do not collect it.

At its core, this theme reflects a privacy concern with implications for all aspects of learning analytics, including LAD research. From the perspective of JEDI, we identify a need for LAD studies to be transparent, use accessible language, and thoughtfully consider all decisions that have to be made by researchers, institutions, staff, instructors, and/or students around how data will be visualized in dashboards [66]. Studies in this literature review exemplify the numerous decisions that must be made when conducting research about data, including but not limited to: who has access to what data; who has access to compare data; what data should be displayed; how should individuals process and use the data; and when can an individual remove themselves from the data. As researchers, so many of these choices have become automatic or predetermined by academic institutions. Even if changes cannot be made, we should still interrogate what those decisions mean for JEDI in the research. Take for example Wise and Jung's [67] paper, they suggest future research should develop a new dashboard view that anonymizes student information to the instructor. In testing these strategies, it is critical to consider how this change might impact JEDI both individually and at an institutional level. Some might argue that hiding the student information can foster equal treatment of all students in the class, while others might argue that student learning is a function of individual student experiences, including their social identities, which should therefore be visible to instructors.

3.3 Implicit Pedagogies

Another theme that emerged is resistance by faculty, and sometimes administrators, to accept dashboard systems because the design does not align with their individual pedagogies. This theme is echoed in many papers in the learning analytics community as a missed opportunity to design educational technologies with pedagogy in mind [16]. Multiple studies found that even with helpful dashboard insights, experienced participants still relied on their own pedagogy to address issues or discrepancies when their interpretation of the data did not align with their own pedagogy [23, 67, 69]. In our sample, we identified studies that focused on integration issues of faculty and advisor pedagogy, and studies that explored how dashboards could be designed with a focus on pedagogy.

Faculty concerns about pedagogy were grounded in the fear that incorporating LADs into teaching might result in extra work for them [5, 14, 31]. This fear is not unfounded, as one of the current issues of learning analytics is the lack of uniformity in data. One strategy to unify the data would be to enforce data standards. For example, if an institution was looking to design a dashboard from LMS data, the designers would need some level of assurance that they could pull consistent data from multiple courses. If one course uses modules to organize course content (e.g., assignments, quizzes) but another course uses pages to organize course content, it becomes challenging to design one dashboard to display the same information for the instructors of both courses. Instead, a course design policy would need to be implemented to choose one of these options as a standard and some instructors would need to adjust their course design and/or pedagogy in order to use the dashboard [28].

Additional workload was mentioned by Wise and Jung [67] as a reason why they did not conduct more interviews with their faculty participants: they thought more interviews throughout the semester would be a burden on the faculty in addition to modifying their courses to use a dashboard. In Howell and colleagues [31], the faculty acknowledged that these decisions might need to be made by the university and compromise was possible, but also felt that faculty should have a seat at the table where these design decisions are being made. In some studies, faculty not only were dealing with the added workload, but also failed to see how the insights from a dashboard could be used to inform their teaching practices [14, 28]. Wise and Jung [67] suggested that faculty might not be able to use dashboards for teaching practices, because they could find the insights incongruent with their observations outside of the dashboard, partly due to the time it takes for the data in the dashboard to update. In these cases, the faculty may lose trust in the dashboard. But not all changes to teaching practices were considered bad, in fact some studies pointed out the opportunity for dashboards to initiate a reflection process for faculty about their pedagogy [28, 67]. Using dashboards in this way could allow faculty to identify ineffective assignments or help them to better adapt their teaching to particular students. These studies show the importance of both incorporating teaching pedagogy into the design of teacher dashboards and using the dashboards as a reflective tool for pedagogy.

While most mentions of pedagogy were directly related to faculty, some papers addressed the pedagogical issues of using dashboards for advising [23, 48]. Gutiérrez and colleagues [23] found that different types of advisors had differing levels of adoption of an advising dashboard. In their study, they compared advising "done by professionals: i.e., trained academic advisers" [23, p. 11] to advising done by faculty. They found that faculty advisors were more likely to trust the dashboard and underlying model as compared to their professional advising counterparts. This difference highlights an issue of pedagogy, because to faculty the LAD was a tool to help them with a secondary responsibility, whereas professional advisors felt their expertise/pedagogy was not fully leveraged by using the LAD. In another study concerning advisor's behaviors with dashboards, Millecamp and colleagues [48] looked at how their dashboard could support advisors meeting with students. They found that advisors typically interacted with the dashboard at the beginning of the meeting to understand a student's situation, but as the meeting progressed, the advisors relied less on the dashboard and more on their pedagogy for helping students. This level of interaction may be sufficient, but it raises the question of whether it is possible to design an advisor-centered dashboard that is useful for the entire advising meeting.

Some of the papers in the sample designed a dashboard to incorporate pedagogy [5, 19]. Echeverria and colleagues [19] set out to understand how a dashboard could be designed with pedagogy as an input in the design process. The result was a dashboard that allowed instructors to customize visualization rules to match their own pedagogy. Unfortunately, these customizations take time to program and additional training would need to be provided to instructors. So it has yet to be determined if this is a feasible solution. While less customized than the previous example, Atif and colleagues [5] found that instructors were willing to put in extra hours to initially configure a system in the hopes that they would be able to deliver a better learning experience to students. The authors cautioned future research to understand the behavior of how and when instructors tweak configurations in order to make future designs more useful.

The emergent issue in this theme is tied to the formal power of faculty, derived from their status in the institution [59]. JEDI-conscious researchers should therefore ask themselves: How might this LAD reinforce and/or support the dominant pedagogy? How does the choice of research questions and design reinforce and/or support the dominant pedagogy? Lastly, what losses can result from forcing individuals into the dominant pedagogy or leaving individuals out of the process? These are hard questions to answer, but grappling with them can yield benefits for LAD research. Looking deeper at Wise and Jung's [67] study, one of their findings highlights that instructors were unwilling to adopt a LAD if its insights contradicted their own knowledge or experience. This dissonance could just be one of many messages signaling to a minoritized instructor that they are wrong, while a non-minoritized instructor may dismiss the LAD insight without questioning themselves. This raises a critical question of how one can design and research a system that proves useful to both instructors without disregarding their experience or knowledge.

3.4 Software Development Resources

The fourth theme that arose from the sample of papers was the scarcity of commercialized or open-source software used to create dashboards. The majority of papers used homegrown dashboards built either by the researchers or in cooperation with their institution's IT departments [1, 3–5, 9, 11–13, 19, 23, 24, 27, 28, 37, 45, 48, 58, 67]. Foster and Siddle [20] contracted their dashboard development to a company and were able to request modifications as a consultant to the company's dashboard software. Brown [14] did not indicate the source of their software, but given the study spanned more than one university, it was likely a commercial software.

There are two sides to the question of whether researchers should use homegrown or commercial software. Homegrown software gives the research team more flexibility to design a usable dashboard for their context along with avoiding adding to the increased commercialization of higher education [16]. However, the homegrown customizations which are benefits in one study context may not transfer well to another institution or study without extensive technical work. This was evidenced by Guerra and colleagues [22], who used the same base implementation of an advisor dashboard across three different institutions. Each institution underwent their own software development to customize the dashboard to their needs. The creation of dashboards is resource intensive in terms of financial and human capital, potentially creating a barrier for researchers trying to conduct LAD research. While commercialized software tends to be expensive, the results and findings from studies using commercialized software may have more potential to be transferable to multiple contexts.

Another option for creating dashboard software that can be scaled is to use open-source software. Only two papers in the sample utilized open-source software to construct their dashboards [39, 44]. Another two open-source software papers were identified in the article search process, but they did not include empirical studies [17, 42]. Implementing an open-source dashboard can be resource intensive, as evidenced by the technology stack and setup of Leitner and Ebner's [42] open-source dashboard software paper. Another study created open-source software to be used with edX and Open edX courses [17]. Where there is no correct correct answer for the type of dashboard software to use for LADs, the financial and technical resources required to conduct this type of work deserve awareness and discussion in the field.

There was also a geographical trend in efforts to create LADs, with a bias towards countries in the global north. The availability of software development resources not only influences how data will be displayed, but also what data that is used in a dashboard. Although study sites spanned across all continents except Antarctica, there still was limited globalization in terms of the number of countries represented. Figure 2 illustrates this point about the global distribution of LAD research. Relying on mostly individualistic countries to set forth what data are important to visualize could have serious consequences for deploying these dashboards in other cultures [41]. We are not the first to note this bias against the global

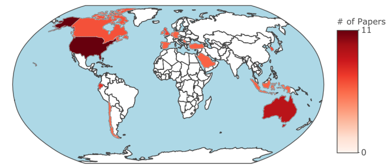

Figure 2: LAD research papers by the country where the study was conducted. The majority of LADs are developed and researched in North America, Europe, and Australia.

south; other education researchers have highlighted the same issue in regards to educational research [40, 61]. With most research sites being located in western cultures, eastern perspectives may be unwittingly excluded in dashboard narratives. This could result in problems if dashboards are deployed at institutions without an evaluation of their local effects. Further research that investigates these issues can further our understanding of the globalization of LADs.

Collaboration can serve as an approach to address JEDI by combining software development resources. Combining resources, through open-source code or formal partnerships, can enable scientists without the necessary resources to conduct LAD research. This type of collaboration is already happening in the LAD literature: Guerra and colleagues [22] and Gutierrez and colleagues [23] deployed dashboards in both European and Latin American countries and added partnerships with research teams from multiple countries. Researchers or institutions who have the resources to undertake LAD development are encouraged to provide open access to the software from the start. While open-source code is a first step, we also acknowledge the significant resources needed to maintain these dashboards. As evident in the sample of papers for this review, many research teams had the support and backing of their institutions. In the near future, this institutional dependency will need to be addressed as a barrier to research progress.

4 DISCUSSION

We conducted a critical review of LAD research focusing on how the literature has engaged with issues of justice, equity, diversity, and inclusion in higher education. We have highlighted four major themes in how research in the broader learning analytics and educational data science community has engaged with these topics thus far. Now we discuss our findings and propose future research directions.

4.1 Current LAD Research for Justice, Equity, Diversity, and Inclusion

Researchers have made substantial efforts to advance our understanding of how to develop LADs in higher education. This presents an opportunity to build upon this body of knowledge to strategically use LADs to improve JEDI in higher education. When we posed RQ1 at the beginning of this investigation, we expected to find and report on LAD research that focused on improving JEDI. Specifically, we expected to present one, if not multiple, themes dedicated to unpacking JEDI in LAD research. However, none of our themes addressed JEDI in LADs, because except for two studies, JEDI concepts were not addressed in any of the papers. Each study had the opportunity to address JEDI, given that all of these studies exist in contexts with issues of power and injustices that have led to groups being underrepresented or marginalized [18]. Foster and Siddle [20] initially considered the use of demographic data, but then they removed all demographic information, except for socioeconomic status, after discussions with their university community raised concerns that these indicators could stereotype students. While critically examining demographics can foster additional concerns, we risk allowing existing inequities to proliferate unfettered if researchers do not pursue opportunities for deeper investigation. In contrast, an exemplar paper that considered JEDI principles, even though the study was not primarily about JEDI, is Li and colleagues [43]. They studied a dashboard that granted instructors the ability to compare student behaviors across predefined subgroups. The purpose of the LAD for this study was not to create a Diversity Dashboard or a dashboard that caters to people with JEDI-specific questions. Instead, this study incorporated JEDI principles by providing a LAD with the flexibility to use it to visualize and uncover disparities in course contexts. This work exemplifies the opportunity to address JEDI questions in research that is not framed as a paper on JEDI.

4.2 Maintaining Systemic Inequities in LAD Research

In recent years, a common institutional strategy to address social inequity has been to create Diversity, Equity, and Inclusion initiatives and offices [52]. Yet these offices are often siloed and unwittingly contribute to a narrative that diversity-related work is only done by individuals working in these offices or for initiatives created by these offices. This problem is further complicated by the gap between those who research education and those who practice education in the day-to-day. This gap between those that conduct research and those that enact the research into practice has contributed to maintaining and exacerbating historical inequities in higher education.

However, LAD research is unique in that it interweaves multiple contexts, uniquely placing the research team in a position to affect the research design and their use of tools in educational contexts. Our thematic analysis addressed RQ2 by highlighting researcher practices that can contribute to maintaining systemic inequities in LAD research. In particular, the sampling and description of participant populations in studies, as well as unspecified researcher positionality; student and faculty-based concerns about surveillance that often remain unaddressed; the implied behavior changes required for user adoption of LADs; and the abundance of resources needed to conduct LAD research. We hope researchers will critically examine their research to understand how their research practices are related to the themes we identified and may contribute to creating or maintaining inequities.

4.3 Future Work

Lastly, we address answers to RQ3 by highlighting opportunities within LAD research to improve JEDI in higher education. We call attention to the following directions for future research that can help to improve LADs.

4.3.1 Shared Software Resources and Cross-Border Collaborations. As we enter a new phase in higher education, where students use technology to study virtually across borders [36], LAD researchers have an opportunity to also cross borders to connect and collaborate. This connection could include partnerships that gain access to new populations or sharing resources to develop new LADs. When researchers collaborate to develop LADs, additional data can be incorporated, and more opportunities for improved practices and pedagogies are possible. Researchers looking to engage in this type of research should look at the LALA project and the lessons learned from this large-scale dashboard collaboration [30]. Two of the studies based on this project were included in this review. Moreover, Hilliger and colleagues [30] present more case studies of this collaboration along with lessons learned from their cross-border collaboration.

4.3.2 Improved LAD Design and Usability. To advance the design and usability of LADs, we encourage more perspectives from users and learning theories to be taken into account. This also means that projects should also consider making LAD development more accessible to researchers and institutions, and adopting more open-source software. Research conducted by Echeverria and colleagues [19] and Atif and colleagues [5] are exemplars for designing LADs with pedagogy as a design requirement. Echeverria and colleagues [19] had instructors create rules related to teaching pedagogy, such as participation in the class discussion board. An example dashboard rule related to this type of participation highlights students who have posted less than a minimum number of postings. To incorporate JEDI into this rule, the LAD could convey to the instructor available demographic information that the highlighted students have in common. This type of design that allows the end-user to create rules based on their pedagogies or needs will also allow for these rules to have JEDI extensions that can highlight previously unknown inequities.

4.3.3 Studying LADs for JEDI. By tackling challenging issues of JEDI, researchers can model how to embed meaningful use of demographic data into dashboards. For instance, Aguilar and colleagues [1] studied a summer bridge program with a high proportion of "underrepresented minorities", but they missed an opportunity to examine or discuss how students' demographic characteristics could have been embedded into their dashboard. At a time when institutions are grappling with how to identify and reduce systematic inequities on their campuses, our research community has an opportunity to take up the call to study how to design dashboards that can advance this goal. Taking advantage of the current momentum to advance social justice, we encourage more LAD research to focus on this critical topic or at least critically engage with the implications of LADs for JEDI. Researchers interested in creating dashboards that center the experiences of historically marginalized students may find inspiration in the Equity Scoreboard project [6, 25]. The project "combines a theoretical framework with practical strategies to initiate institutional change that will lead to equitable outcomes for students of color" [62], and at the end of the process, a dashboard is created to show context-specific metrics for long-term evaluation of initiatives. While this project concentrates on macro-level institutional data, the practices from this project can be adapted to more granular, course-level data, which are more representative of LAD data.

4.4 LAD Research that Does Not Focus on JEDI

Every research study sets out to address a set of research questions and this does not require a focus on JEDI. One purpose of this review is to continue the conversations started by many organizations via "Call for Actions" statements. SOLAR's Statement of Support and Call for Action in 2020 included such a call to their research community: *"We encourage members of our Society to mobilise our expertise and connections with communities to actively contribute to the hard work of promoting social justice and dismantling injustices in education. [...] It is our duty to educate ourselves and to focus more actively on how to create an equitable and just environment for all academics, and people our work impacts, free from racial discrimination."* [56]

Our interpretation of SOLAR's call to action is to examine how all research, regardless of its research questions, can actively help dismantle injustices in education. Previous research has documented the issues that can occur when JEDI is merely a symbolic notion without active prioritization [51, 52]. Our goal in highlighting specific studies as having missed opportunities to engage with JEDI is not to suggest that the research questions in these papers should change, but to indicate places where small intentional changes could actively help dismantle injustices in education.

4.5 Limitations

This study is a critical review and therefore subject to the limitations of a critical review. It cannot be compared or used like a systematic literature review because we used a sample of papers addressing a specific concern. This limitation does not invalidate a critical review [50]. Moreover, a critical review is dependent on the researchers and their experiences when creating themes. As a US-born doctoral student with multiple US underrepresented and minoritized identities and a European-born professor now living in the US, our results were constructed through these lenses. Once again, this does not invalidate the review, but it allows our readers to further contextualize the results for their purposes.

5 CONCLUSION

We sought to understand the potentially significant benefits of LADs are being leveraged to improve JEDI in higher education. Through a critical literature review, we identified four areas in LAD research where changes could be made to improve outcomes for justice, equity, diversity, and inclusion. Our findings support one conclusion in particular: there is a need to incorporate JEDI research into LAD studies. There are many ways, identified here through our themes, for researchers to incorporate JEDI into their studies, and without having to change the focus of their scientific inquiry. They range from the simple addition of details about participants so that policies based on research studies are applied in appropriate contexts, to the harder effort of recruiting more diverse participants early in the research to understand pedagogical issues and needs of the faculty, staff, and students using the dashboards. Another more complex recommendation, but one that can be strategically underwritten by funding agencies, is to create cross-cultural and cross-boundary collaborations that allow LADs and LAD theories to be tested in multiple contexts. Most of these directions for future work can be addressed immediately and the list is certainly not exhaustive. We are keen to see our field use JEDI principles to promote justice, equity, diversity, and inclusion in LADs and, more generally, in learning analytics.

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