Coding Bias in the Use of Behavior Management Technologies: Uncovering Socio-technical Consequences of Data-driven Surveillance in Classrooms

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ABSTRACT

Digital educational technologies have been employed in classrooms to collect students' behavioral data in the hope of supporting teachers in identifying and correcting undesirable behaviors, which raises the concern of heightened surveillance in classrooms. We present a qualitative study of 20 K-8 teachers to understand their experiences and practices of using ClassDojo, a data-driven classroom behavior management intervention. Our analysis reveals a series of unintended socio-technical effects resulting from the use of ClassDojo in practice. In particular, the use of ClassDojo runs the risk of measuring, codifying, and simplifying the nuanced psycho-social factors that may drive children's behavior and performance, thereby serving as a "Band-Aid" for deeper issues. We discuss how this process could perpetuate existing inequality and bias in education. With the goals of spurring future design and mitigating these unintended effects, we take on the reflexive-interventionist approach and propose three considerations for designing and using future educational technologies: 1) provide context, 2) expose bias, and 3) challenge and reimagine what is normal.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in collaborative and social computing**; *User studies*; • **Social and professional topics** → *Surveillance*; • **Applied computing** → *Education*.

KEYWORDS

Behavior management; educational technology; ClassDojo; surveillance; bias; inequality; unintended consequences

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> "*When bias and inequality come to light, 'lack of intention' to harm is not a viable alibi. One cannot reap the reward when things go right but downplay responsibility when they go wrong.*" – Ruha Benjamin [11, p.76].

1 INTRODUCTION

Digital technologies have greatly transformed the landscape and capacity of modern education and pedagogy. Today's schools and classrooms are wired with varied learning management tools, adaptive learning software, and sensing technologies to support both teaching and learning activities. Researchers and practitioners in human-computer interaction (HCI) have long designed varied educational interventions and investigated their promises in supporting teaching and learning activities [21, 24, 45, 66, 69], home-school collaboration [55, 83], children's social-emotional skill development [68], teachers' professional development [3], and behavior management and intervention [42, 56, 70]. While these educational technologies have become increasingly data-driven, they have been shown to provide teachers and practitioners with evidence-based insights into students' learning process and the effectiveness of teaching [23, 50]. Data have also been used to predict learning outcomes and tailor educational interventions to individuals' needs [18]. One salient type of intervention focuses on facilitating classroom behavior management and is considered effective in supporting students' psychosocial development and long-term outcomes [47, 55, 70].

Yet, recent critical scholarship in education and pedagogy has started raising concerns about heightened surveillance and threats to privacy resulting from educational technologies' pervasive collection, processing, and aggregation of student data [5, 81]. Such data range from students' attendance, grades, and assessment scores, to students' embodied behavior and conduct in the classroom and school. For example, a number of recent reports underscore that the widespread use of facial recognition cameras in schools normalizes surveillance and control in classrooms and schools, while these cameras are often adopted to support school security and safety [5, 37, 67]. Close analysis of such pervasive technologies reveals their potential to disproportionately burden students experiencing marginalization due to their backgrounds [37]. To fully study the effectiveness of data-driven educational technologies, therefore, should look beyond their intended practical role in teaching and critically examine the socio-technical consequences that such technologies can unfold in practice [81]. However, while HCI scholars have long been interested in the promise of technological interventions in schools and classrooms (e.g., [55, 68–70]), less attention focuses on the unintended consequences of these systems [49, 63].

In this paper, we present a case study of ClassDojo to unpack the unintended socio-technical consequences resulting from the use of data-driven behavior management technologies. We focused on ClassDojo because it is arguably the most popular digital intervention for classroom management [53]. Similar to the logic of past data-driven behavior management interventions designed by HCI researchers [70], ClassDojo allows teachers to tokenize, quantify, and document student behavior in the class and communicate with parents. Teachers can reward students with Dojo points to encourage desired behaviors such as working hard and being kind, and take points away from students to discourage undesired behaviors like talking during instruction and being disrespectful. While ClassDojo aims to "help every teacher create an incredible classroom" and "give their kids learning experiences they love" [22], a growing body of work by researchers and activists alike criticizes behavior management technologies like ClassDojo's role in replicating and extending the logic of Foucauldian panoptic surveillance on students' conduct and behavior (e.g., [10, 53, 79]). Yet, the empirical understanding of how the socio-technical consequences of such classroom surveillance unfolds are still scant [48, 53].

To address these gaps, we held in-depth interviews with 20 kindergarten to grade 8 (K-8) teachers to understand their practice of using ClassDojo in the classroom. Our analysis was guided by the following research question: *What are the unintended consequences of data-driven behavior management technologies on children?* Our results reveal a number of specific social-technical challenges and concerns resulting from teachers' use of ClassDojo and monitoring of student behaviors. We found that teachers' existing bias on students can be reinforced and institutionalized in this process. Drawing insights from emerging debates amongst HCI, science and technology studies (STS), and adjacent fields, we discuss how certain types of human actions, social norms, and states of being are endorsed, privileged, and normalized in the use of behavior management technologies, while the existing disadvantages can be further amplified. Finally, we took a reflexive-interventionist approach as developed by Lindtner et al. [51]. This reflexive-interventionist approach allows us to simultaneously critique the presence of educational techno-solutions to identify opportunities for intervention and speculate alternative futures. In this spirit, we offer three considerations as a first step for HCI designers and practitioners designing future educational technologies to mitigate such unintended socio-technical effects going forward, including 1) providing context, 2) exposing bias, and 3) challenging and reimagining the normal.

This empirical understanding of educational technologies' and data-driven surveillance technologies' unintended consequences is critical to our field. Investigating how these systems exacerbate inequalities allows HCI researchers and practitioners to design fairer and more inclusive tools going forward.

2 RELATED WORK

To situate this study, we first review existing studies on designing and implementing educational systems in the classroom and the growing critiques on the datafication of student behavior. Thereafter, we discuss how teachers' expectations impact students' short-term and long-term psychosocial development and the broader issues of bias in education.

2.1 Technology Use in Classrooms and Datafication of Education

Scholarship in HCI and adjacent fields have designed and assessed educational technologies to support teachers' and students' varied needs (e.g., [24, 45, 66, 68–70]). With the advancement of data-driven technologies, HCI researchers have shown the benefits of data-driven educational technologies in supporting students' individual needs [18] and practitioners' collaborative reflections [54]. Marcu and Spiller recently developed a model of collaborative data collection for behavior intervention in the classroom, highlighting data's critical role in tracking students' progress towards behavioral goals, setting up long-term intervention plans, and enabling close real-time monitoring [56].

Yet, there is a rising concern over the surveillance and privacy issues brought about by these data-driven technologies in HCI (e.g., [49, 63]). For example, Kumar et al. argue that data-driven learning management technologies' productivity software has become an essential part of today's elementary schools and classrooms [49]. Through nine focus groups with 25 teachers, these authors highlight the importance of including privacy features and lessons in data-driven learning management technologies to raise both educators' and students' awareness of this subject matter [49]. In addition, while acknowledging the potential abuse of data-driven classroom sensing technologies in invading students' privacy and leading to inaccurate perceptions of students, Ogan highlights the potential of these technologies to empower teachers to improve their decisions and practices in the classroom [63]. The author proposes a series of guidelines for the ethical use of classroom sensing and stresses the importance of utilizing data for improvement rather than evaluating students' capacity.

Another growing line of critical scholarship inquires into the controversial datafication of student *behaviors* in schools and classrooms. In the context of the U.S., the systematic emphasis of behavior management as teachers' and schools' primary goal is deeply intertwined with the neoliberal school reform [76]. Scholars have criticized behavior management's role in reproducing the top-down logic of control and discipline in classrooms [7, 76]. Under this logic, "difficult" students' disruptive behavior is punished and the normative behavior of "good" students is rewarded and encouraged; importantly, this construction of "good" and "difficult" students is racialized and reflects the interlocking system of marginalization [7, 14]. As a result, students who do not conform to normative whiteness are more likely subject to discipline and to be funneled into the school-to-prison pipeline [6, 59]. In this light, Manolev et al. coined the term "the datafication of discipline" and criticized that behavior management technologies like ClassDojo naturalize the data-driven surveillance logic in the education context and lead to the culture of performativity [53]. Williamson's critical investigations similarly suggest that ClassDojo functions as a "behaviorist surveillance machine for the classroom" that facilitates teachers' psychological surveillance on children and therefore modifies their social-emotional learning in classrooms [79, p.445]. In particular, ClassDojo's point system makes it successful in "compelling children to conduct themselves in ways appropriate to the development of those normative qualities" through rewarding compliance and obedience [80, p.19]. In fact, recent studies suggest that ClassDojo allows teachers to collect more student data than traditional paper-and-pencil note-taking, but raised concerns about inequality of access among families with lower socioeconomic conditions and public shaming on students [48].

Taken together, it is still unclear how these aforementioned critiques and concerns on data-driven behavior management technologies manifest in the classroom environment [53]. Our work extends this line of research by offering an empirical understanding of the unintended socio-technical consequences resulting from classroom surveillance mediated by behavioral management technologies.

2.2 Teacher Biases In the Classroom

Prior research in the field of education has shown that teachers' practices and pedagogies can be influenced by their perceptions and expectations of students. For example, Brophy and Good's early work illustrate that teachers communicated and interacted with students in different ways based on their expectations of each respective student [15]. Such differential perceptions of students can be informed by a wide range of information and channels, including students' gender [65], race and ethnicity [72], socioeconomic status (SES) [78], and dis/ability [61]. Such biases in teacher expectations have shown to be highly situated in the classroom context. In particular, McKown and Weinstein found that teachers tend to be more biased when the classroom is more diverse, and teachers tend to have lower expectations of children from stereotyped ethnic groups with similar achievement records as their peers from non-stereotyped groups [58].

Past studies have shown that teacher biases and perceptions can impact children's achievements and outcomes, especially among children from stereotyped and marginalized groups, both in the short- and long-term. In particular, besides student academic achievements, Zhu et al. recently suggested that teachers' low-level expectations of students, together with negative teacher feedback, can lead to lower psycho-social outcomes among students, such as less motivation for achievement and a growing sense of shame [84]. Researchers have also highlighted that students tend to internalize teachers' judgment and biases, and thereby perform consistently with their perceived expectations [77, 84]. As such, students with marginalized backgrounds tend to be more vulnerable and susceptible to teacher bias [57, 58].

In this light, with the proliferation of data-driven educational technologies, it is still unknown whether and, if so, how teacher biases play a role in the data-driven surveillance of student behaviors. HCI researchers have long been concerned about the bias of socio-technical systems (e.g., [17, 20, 33, 36]). Most of these studies, however, focus on issues of bias and fairness built into the design and operation of systems and algorithms. This current study contributes to this line of research by scaffolding how human actors' expectations and biases are being mediated and replicated through their use of socio-technical systems (e.g., [4, 39]). This knowledge will help future HCI researchers and practitioners better mitigate the unintended consequences that educational technologies may unfold in practice.

3 METHODS

To answer our research question, we conducted in-depth interviews with 20 teachers who were teaching students from kindergarten to grade 8 (K-8). This qualitative method allowed us to better understand the different ways in which teachers used platforms and their associated motivations and challenges. Overall, the nature of the semi-structured interview method allowed flexibility for participants to share their thoughts and enabled us to uncover topics that we did not previously consider in our protocol.

3.1 Participant Recruitment

To be eligible for our study, participants needed to (1) have experience as teachers working in elementary and middle schools and (2) have been using behavior management technologies, such as ClassDojo, in the classroom setting. To recruit participants for interviews, we posted on Reddit subgroups and Facebook groups for teachers. Also, we asked our participants to introduce other likely candidates for the study. To examine prospective participants' eligibility, they were asked to complete a screener based on the aforementioned requirements. Our study was approved by the university's Institutional Review Board (IRB).

Our participants included 19 current teachers (13 were teaching in elementary school grades K-5, and six were teaching in middle schools grades 6-8), and one former teacher who was currently working as a technology consultant, supporting teachers' technology use across a middle school. Most of our participants were working in public schools (n=17), and three were working in private schools. The majority of our participants were women (n=17), and three were men. Our sample biases women, which aligns with the statistical fact that nearly 80% of public school teachers in the US are women [75].[1] Although we did not particularly target teachers who taught a diversity of students, 15 teachers reported working in urban school districts with relatively high poverty rates, and nine teachers reported working in schools with a large number of students from immigrant families.

3.2 Data Collection and Analysis

We held in-depth semi-structured interviews with 20 participants. Due to the Covid-19 pandemic restrictions, all interviews were conducted online by the first author through Zoom, Bluejeans, and Google Meet video calls between March and May 2020. On average, our interviews lasted 75 minutes (max=134 minutes; min=47 minutes), and each participant received a $20 Amazon gift card as

[1] In the U.S., the teaching profession has historically been women-dominate since the establishment of the public school system [82]. The gendered role of teacher's work is deeply rooted in the discursive construction and the maternal imaginaries of teachers and teaching [1], which renders teacher's work under-credited and invisible.

compensation for their time. All interviews were audio-recorded and transcribed, and we received oral consent from our participants at the beginning of the study.

Interviews included questions about teachers' motivations for using behavior management technologies, how they tracked students' behavioral data through the system, what they liked and disliked about the point system and the rewarding mechanism, and how their expectations and judgments of students impacted and had been impacted by their use of the system. Teachers were also primed to think about how they utilize the behavioral analytics and reports generated by these technologies, and how their use of these tools impact their practices in the classroom. We also invited participants to reflect on issues related to fairness and bias in their past use of ClassDojo. The first author kept running notes during the process of data collection. Such memoing practices allowed us to identify early patterns, update the interview protocol, and facilitate communication among research team members [12]. Finally, we conducted member checking with eight of our participants who responded when we reached out between August and October 2020, to have a follow-up phone call in which we shared and validated our findings.

We analyzed our interview data through reflexive thematic analysis, which was a suitable approach to address the research question [13]. Also, this approach allowed us to identify patterns across a dataset without trying to fit the themes into pre-existing theoretical frameworks. In particular, the first author conducted the first round of coding in Atlas.TI by reviewing our transcripts and memos and converting the text into codes. Throughout this process, the research team discussed and reflected on the generated codes on a weekly basis. The salient codes we identified in the first round of coding include: target particular students, teacher bias, the conflict between universal measure and nuanced behavior, and complex underpinnings of student behavior. Thereafter, the research team conducted another round of focused coding. Using affinity diagramming, the team reviewed and defined themes related to teachers' nuanced and situated experience of using behavior management interventions in the classroom. In this paper, we focus on how teachers' biases impacted their use of the ClassDojo system and the resulting unintended consequences.

4 KEY AFFORDANCES OF CLASSDOJO

In order to better contextualize our findings, we first describe the key affordances of ClassDojo, focusing on the socio-technical aspects of the system.[2] Doing so will help us to unpack the nature of surveillance embodied in the design and use of ClassDojo and to examine its unintended effects.

As noted earlier, ClassDojo is arguably one of the most popular educational technologies employed in K-8 schools for the purposes of behavior management and home-school communication. While we do not have detailed statistics of ClassDojo's user group size, the platform's official website claims that the tool has been adopted in over 95% of K-8 schools in the United States.[3] Overall, ClassDojo is free and easy-to-use. Teachers can use the software on their smartphones, tablets, laptops, and interactive whiteboards in the classroom.

ClassDojo's key feature lies in its point system, which allows teachers to categorize and define desired (i.e., "positive") and undesired (i.e., "needs work") behaviors in the classroom (see Table 1 for detailed description). Teachers can assign quantified "Dojo points" to each behavior parameter based on their perceived importance. ClassDojo's point system also allows teachers to directly monitor, document, and track the whole-class' and individual students' behavior based on their observation and interpretation. They can simply click the student's avatar to give Dojo points for particular pre-defined desired behavior parameters and take points away for pre-defined undesired behavior parameters (see Fig. 1d). This is accompanied by immediate audio and visual feedback to teachers and students—desired behaviors are labeled in green (see Fig. 1a) and accompanied with a satisfactory "ding" sound effect, whereas undesired behaviors are labeled in red (see Fig. 1b) and accompanied with a harsh "dang" sound effect. Teachers can view the daily and weekly reports of the whole class and individual students. The report can illustrate the number of accumulated Dojo points, the detailed breakdown of these Dojo points, the specific time at which the Dojo points were rewarded or penalized, and the overall trend of the Dojo points (see Fig. 1e).

Moreover, besides teachers and students, ClassDojo involves multiple actors around the matter of behavior management. In particular, parents can log in to ClassDojo on their phones to check their children's performance in the classroom. Parents are able to communicate with teachers through the direct messaging feature and receive real-time notification when their child acquires or loses Dojo points [31]; and school administrators can join ClassDojo to connect with teachers and parents [30].

Together, the datafication and direct monitoring of students' behaviors embody a logic of surveillance and discipline in the classroom [53], an aspect that is overlooked in the past HCI research on educational technologies. Investigating teachers' lived experiences of using ClassDojo in the classroom gives us a unique opportunity to critically uncover its unintended consequences beyond the intention of "foster positive student behaviors and classroom culture" [31].

5 FINDINGS

Teachers' everyday job was multifaceted and demanding, which often led to extra emotional labor. Our participants reached the consensus that teaching and preparing curriculum was only a small part of their job. Taking care of students' safety and supporting individual growth in the school setting were deemed as teachers' central focuses. Therefore, our participants described behavior management as the most critical part of their practices in the classroom. They described behavior management as an encapsulation of necessary foundations for their "*actual teaching*" (P4) and students' "*actual learning*" (P17) in the classroom. However, teachers cited behavior management as a challenging task as there was no silver bullet solution. Our teachers had to adjust their strategies based upon the student body they were working with. To aid in this, teachers turned to techno-solutions to support and simplify this complicated process. As the most popular data-driven behavior

[2] The study was conducted from March to May 2020. We describe the system as of the time of the study, and as a result, changes since are not discussed.
[3] See https://www.classdojo.com/press/, last retrieved February 2021.

Table 1: Summary of ClassDojo's key affordances

Key Affordances	Description
Categorizing and quantifying desired and undesired behaviors	• The platform suggests a series of default undesired "needs work" behaviors (e.g., "off task," see Fig.1a&1c) and "positive" behaviors (e.g., "on task," "working hard," see Fig.1b) and assigns a certain number of Dojo points to each behavior parameter (from 0 to +/-5 points, see Fig.1c) • Teachers can customize and tailor the behavior parameters and their points to specific needs and expectations of the class
Monitoring, documenting and tracking student behaviors	• Teachers can set up a profile for each student in the class. Each student is represented by a unique Dojo "monster" as the avatar • Teachers can reward points to or take points away from students by manually documenting students' conduct in the class on their phone, tablet, or laptop • Teachers can view the whole class's and individual students' behavior report in a specific time frame as donut charts (see Fig.1e)
Providing feedback on student behaviors	• ClassDojo provides audio feedback to student behaviors: when any desired behavior was documented, the system would play a positive "ding" sound effect; undesired behavior is accompanied by a negative "dang" sound effect • ClassDojo provides visual feedback to student behaviors: desired behaviors are color-coded in red and undesired behaviors are color-coded in green. Similarly, students are labeled in green or red based on their Dojo points (see Fig.1d)
Connecting with parents and school administrators	• Teachers can send whole-class and direct messages to students' parents • Parents can receive real-time notification when their children gets/loses points • School administrators can also sign up for their own ClassDojo account and connect to teachers and parents

management system, ClassDojo was and had become the "go-to solution" for classroom management in elementary and middle schools.

In the following sections, we address our research question by unpacking how teachers' biases and perceptions were shaping and being shaped by their use of ClassDojo, and how this process impacted students based on teachers' observations. In our interview, P10 drew a parallel between ClassDojo and Band-Aiding, or creating a makeshift fix for deeper issues, to describe how she regarded ClassDojo as a go-to techno-solution to fix behavior management issues:

> *Earlier on in my career, I really was trying to use [ClassDojo] as a "Band-Aid" over an issue that was bigger than just a little point system would actually address. [...] But the reward point system as a part of the behavioral management is just the very least of what actually makes a difference.* (P10, W/7th-8th)[4]

A Band-Aid can serve as a simple solution or short-term cure. However, applying a Band-Aid could mask the root causes of issues found in the classroom and give the illusion that further treatment is no longer needed. In this spirit, we rely on the metaphor of the "Band-Aid" to discuss the unintended consequences that ClassDojo and its data-driven surveillance logic unfolded. Specifically, we first document how ClassDojo's quantification scheme simplifies and decontextualizes students' lived experiences and complicated psycho-social underpinnings of behavior in the classroom. We then describe how interactions between teachers and students could be overlooked in the use of ClassDojo. Thereafter, we identify various instances of how teacher bias can be replicated and reinforced in this process. And finally, we discuss how this process could lead to unintended psychological impacts on students. Together, our findings illustrate how certain behaviors, norms, and types of interactions were being privileged under classroom surveillance, while others were being disadvantaged.

5.1 Simplifying What's Behind the Data Point

Leveraging ClassDojo's quantification of behavior and point system, our participants hoped to alleviate and simplify their labor in the complex process of behavior management. Doing so allowed teachers to document and track students' behaviors in an effective way. With ClassDojo operating on their devices, teachers could immediately reward Dojo points and take points away based on pre-defined behavior parameters whenever they observed students performing certain behaviors. However, in doing so, we found that ClassDojo and its point system had become a tool for some teachers to "*shut down*" (P14) certain undesired behaviors and cover up what was actually happening within the classroom and beyond, leaving the root causes unattended to.

5.1.1 Decontexualizing Student Behaviors. Simply clicking on pre-defined behavior categories to reward or penalize student behaviors afforded teachers the ability to measure the dichotomy of "*whether the expectation is met or not*," as articulated by P15. Yet, some teachers who highlighted this dichotomy essentially rejected seeing students' behaviors as a spectrum in practice. Instead, there should be no clear boundary between whether a particular behavior in the

[4]Participant's demographic information is formatted as Gender/Grades

Figure 1: Screenshots of ClassDojo: a) example of "needs work" behavior parameters, b) default "positive" behavior parameters, c) adding/editing behavior parameters and adjusting corresponding Dojo point weight, d) class dashboard view, e) weekly behavior report for individual students and class as a whole. ©ClassDojo

classroom was right or wrong, positive or negative. For example, P4 was a chemistry teacher at an inner-city middle school with high poverty rates. She explained how the seemingly straightforward undesired behavior of "being disrespectful" was complicated in practice:

> *You could take a point off of a kid for "being disrespectful" - [that could mean anything from] calling a student a name or throwing a chair at another student. You don't actually know how bad that disrespect was unless you put super specific things in your point values that you make. I think it just gives a snapshot of behavior. I don't think it gives a reflection of the student as a whole.* (P4, W/7th-8th)

As this quote suggests, data points collected by teachers on ClassDojo were often decontextualized. Students' qualitative experience in the classroom was forced to be categorized under pre-defined behavior parameters and quantified into Dojo points. P5, a teacher at a Title I public elementary school[5] echoed this quote and similarly stressed that "*behavior is always superficial*" and subject to teachers' speculation and interpretation. This is to say, the use of ClassDojo's point system divorced student behaviors from their everyday reality, which was then assessed, recast, and inculcated by teachers.

5.1.2 *Overlooking Complicated Underpinnings of Student Behaviors.*

Oftentimes, students' misbehavior in the classroom could be brought about by complex psycho-social and emotional underpinnings, and a lot of these driving factors might be out of students' control and happening outside the school itself. According to our participants, many behavior issues in the classroom have emerged from factors related to their family, including the household's socioeconomic status, parenting style, family structure and dynamics, cultural values, and more. And these complex and diverse factors could be embodied as seemingly similar undesired behaviors in the classroom and result in the same negative points on ClassDojo. P18, for instance, was a K-2 teacher at an inner-city community with high poverty and crime rates, and she reported working with children from families with low socioeconomic status. She took the common behavior of "not focused" as an example, and outlined a series of possible external driving factors that were not able to be captured by surveillance through ClassDojo:

> *Those numbers are so open to interpretation. [...] most of the kids who have bad behavior have a problem where*

[5]In the U.S., schools with over 40% of students from low-income families are eligible to receive Title I funds. The Title I funds can be used to develop and operate school-wide programs that support all students in the school, which aims to improve the educational outcome of low-achieving students. See https://www2.ed.gov/programs/titleiparta/index.html, last retrieved April 2021.

> *they cannot control themselves. Their blood sugar is too high, they're dehydrated, they're not eating well at home, they're not sleeping at night. And what are we going to say with the ClassDojo? We're going to fix it? No, we're not.* (P18, W/K-2)

As indicated in this quote, using ClassDojo could lead teachers to attribute student misbehavior to individuals, while what's behind the data point was simplified and overlooked. In this case, P9 pointed out that misbehaving in the classroom could be a way for some students to send signals to their teachers, in order to seek more attention. Shutting down and penalizing such signals through ClassDojo, however, could reject the opportunity to provide care and support.

Additionally, the cultural norms that students had been growing up with could determine whether they view certain behaviors as "normal." Yet, these norms did not necessarily align with ClassDojo measures informed by teachers' situated social norms and expectations. In the interview, P10 took the seemingly universal measure "being respectful" as an example. She pointed out that students from different cultural backgrounds could interpret "respectful" in different ways: "*so if you come from a big family where people just take stuff, somebody walking by your desk and picking up a pencil may not bother you.*" Moreover, as stressed by P15, such misalignment of norms between teachers and students could make "*normative behavior become super pervasive and bleed into what we think makes a good student.*" In other words, measuring students against the narrow standards of acceptability upheld a specific and culturally defined logic, thereby punishing students who deviate from dominant social norms.

5.1.3 Penalizing Students with Dis/abilities. In some cases, students' dis/abilities could greatly impact how they behave in the classroom. Taking a common ClassDojo behavior parameter of "not talking out of turn" as an example, some participants highlighted that this could be especially challenging for kids with ADHD when they did not have the capacity to control their voice. For example, P8 was a veteran teacher at a public elementary school, and she told us:

> *If you have challenging students in the classroom, you know they're not on medication, you suspect that they might be ADHD or ADD. [...] But you're penalizing them for something that is beyond their control. So, that's another reason why I really don't like ClassDojo, [...] because teachers are going to end up punishing a child that can't help it. It's beyond their control. So why bother? I mean, this is not going to help.* (P8, W/K-2)

Again, as this quote suggests, ClassDojo's point system did not make space for teachers to take students' varied needs into account, and the resulting data point could not reflect why these students might behave in certain ways. In effect, teachers might heighten their scrutiny over students who were labeled as having dis/abilities because they were not able to behave as other "normal" students.

Altogether, we see such simplifications could turn classroom surveillance into Band-Aiding undesired behaviors and overlooking students' situated experiences and specific contexts of families, values, and backgrounds. In this way, we argue students' ways of being were under scrutiny based on the constructs around them. The education of a child could become the management of their constructs and the quantification of those constructs.

5.2 Overlooking Human-to-Human Interactions

Developing relationships with students via meaningful interpersonal interaction was deemed critical for pedagogy. Some teachers believed this step allowed them to develop bonds and trust with students and thus better support their individual needs. However, our interviews with teachers revealed such human-to-human interactions could be overlooked in the use of ClassDojo in two ways: 1) such interactions were devalued and perceived as unnecessary, and 2) students who needed such interactions were rendered invisible under surveillance.

5.2.1 Devaluing Human Interactions. In our interviews, our participants pointed out that having the ClassDojo point system in place could give some teachers the illusion that behavior management was all about "*willy nilly giving or taking away points*" (P14). As noted earlier, teachers expressed that taking points away on ClassDojo could shut down students' undesired behaviors in an efficient way. However, just as a Band-Aid covering up wounds is a temporary fix, thorough treatment and care of the wound is necessary to deal with the aftermath and the causes of the problem. Since shutting down undesired behaviors through the Band-Aiding process could sometimes provide an immediate effect, there was potential for some teachers to believe the illusion that students' behaviors were under control and no further support was required of them. P17 described her observations:

> *A teacher might think their job is just to document what you do with [ClassDojo]. Okay. I put everything in, I put in points, I took away points, I'm going to go home. No, that's just something that's like a placeholder. This is a problem we have to work on here. That's the teaching part.* (P17, W/2nd)

As suggested in this quote, human interaction and connection would be critical in identifying students' individual needs, their behavior's root causes, reconciling the potentially negative message sent through the point system, and facilitating social-emotional learning, which was by no means equal to adding or taking points away on ClassDojo. To this end, P9 discussed leveraging the behavior trend to "*figure out a strategy for students who need improvement.*" P9 had been working closely with a group of students with dis/abilities, and she explained the long-term benefits of sitting down with the student and helping them reflect on their Dojo behavior record in adjusting and achieving students' Individualized Education Program (IEP) goals.[6] Another elementary school teacher similarly noted that this extra step should be the key to make behavior management "*sustainable*" and "*authentic.*" Otherwise, the purpose of behavior management could be displaced. She said:

[6] In the U.S., Individualized Education Program (IEP) is mandated for all public school students who receive special education and relevant professional services, which aims to support educational outcomes for students with disabilities. Each student has their individualized IEP goals designed collaboratively by teachers, school administrators, parents, professional service providers, and the student themselves when appropriate. See https://www2.ed.gov/parents/needs/speced/iepguide/index.html, last retrieved April 2021.

> *For me, [...] by looking at the data, you want to figure out a strategy for students who need improvement. That's the main goal for teachers. It's not about you wanting to put a certain [score] for certain students, good or bad. That just defeats the purpose.* (P5, W/1st-5th)

And yet, this participant went on and disclosed that this key process was often overlooked and omitted in teachers' practice because "*that takes a lot more work,*" on top of teachers' already exhausting working tasks in a resource-constrained school district. These findings of devaluing human interactions resonate with prior HCI discussion on *data-as-care* [46], in which the care process is codified and reduced to the management of one's data. In our case, we see managing students' behavior data on ClassDojo could reduce the complex interaction between teachers and students, and consequently displace the valuable opportunity of sensemaking and learning.

5.2.2 Neglecting Invisible Students. In addition, our participants pointed out that the use of the point system rendered some students invisible under classroom surveillance, in contrast to the hypervisibility of students who were constantly rewarded or penalized by teachers. P18, for instance, reflected on her use of ClassDojo and admitted that she unintentionally ignored some students who were relatively quiet in the class:

> *Then sometimes you just give [students who pop up on your radar] a point, you give them a point but [you're] not really looking at the quiet kid that's not really trying to be showy. The kids that kind of go sometimes unfortunately unnoticed because they're so quiet and they're just sitting there.* (P18, W/K-2)

As this quote suggests, this group of quiet students might not have data entries on ClassDojo because they did not perform any pre-defined desired or undesired behaviors. In this case, no data entry meant no data-as-care, which might result in their exclusion from further engagement with teachers and degrade their educational opportunities.

Moreover, the seemingly perfect Dojo score by no means implied one was free of struggles. P20, for instance, said, "*You look like you're an awesome student, but underlying, teacher needs to intervene because there's other problems.*" Our participants admitted that they sometimes failed to recognize these students' potential psycho-social needs due to their "perfect" Dojo points on paper. As suggested in these quotes, ClassDojo was not able to accommodate all these nuances. This is to say, behavioral management was a complicated task involving a lot of labor, and a point system could not single-handedly address the problem.

In sum, unlike measuring student behavior through ClassDojo, building human-to-human relationships to support individual students' needs involved judgments that were contextual and subtle; what ClassDojo's point system afforded, in contrast, was schematic, general, and universal. Put differently, these quantified measures and points could no more reflect teachers' labor in developing relationships with students to identify and mitigate root behavior issues than they could reflect the actual complexity of the student's experience.

5.3 Replicating and Reinforcing Biases in the Use of Technology

As P1 put it, "*There's always that element of you're a human, sometimes you just don't like someone.*" All of our participants acknowledged that having certain judgments and biases toward students was inevitable. Our analysis showed that teacher's use of ClassDojo reproduced such bias in the data-driven surveillance in classrooms. Meanwhile, ClassDojo's audiovisual feedback and connection with other stakeholders could serve to reinforce and institutionalize bias on a systemic level.

5.3.1 Targeting and profiling. Confirming past findings on teacher biases, our analysis suggested that teachers' biases could be informed by students' race and ethnicity, labels of dis/abilities, gender, past behavior records, and more. These biases were sometimes manifested as teachers' intentional targeting and profiling on ClassDojo and heightened scrutiny toward stereotyped students. On this note, some teachers confessed to expecting certain students to act in particular ways and "*be ready to look for*" opportunities to take points away on ClassDojo, simply because these students fall under the presupposed categories. P6, for instance, was a dual-language teacher working at a public middle school with over 80% racial minority students. She acknowledged that white teachers might target Black male students when they were using ClassDojo:

> *It sounds awkward because I'm a white teacher, but unfortunately, most of us are white females. [...] I think because a lot of us are white females, I think a lot of the African American male students who can be louder, who are quicker to stand up and react, I do think they get more negative attention.* (P6, W/6th-8th)

Another example, which similarly depicted how Black and brown students were hypervisible under such disproportionate surveillance, was found in a quote of P10. P10 identified herself working in a public middle school with disadvantaged students from diverse racial backgrounds. In the interview, she was being vocal about witnessing her co-workers targeting Black and brown children on ClassDojo:

> *If you are already consciously or unconsciously primed towards thinking that Black girls are loud and boisterous, and so you're already looking for, "Hey, sit down, be quiet." Or our little Black and brown boys are rough and disruptive and rude and all these other things. Then you're already primed towards any little thing, and then that becomes this thing that gets escalated.* (P10, W/7th-8th)

This participant continued and described how teachers in her school labeled students on ClassDojo based on their stereotypes. She said, "*We've all had kids [with behavior issues]. You see another type of that kid come into your classroom, and you're like, 'Oh, I've seen this kid before. [...] these kids are all this, these kids are going to be that'.*" Such classification, in a way, could push these students to behave in accordance with certain presupposed narratives. Teachers' biases and students' undesired behaviors thus formed a cycle in which two factors reinforce one another. ClassDojo, in this case, could become the catalyst that facilitates this self-fulfilling prophecy through perpetuating these pre-existing biases and disadvantages in practice. Another teacher similarly described this process:

> *They're already looking for the negative interactions and they're already ready to shut everything down by [using] the points. So it becomes cyclical, because for some of those kids, if you're yelling at them in the hallway every single morning, [...] that's not how anybody wants to start their day, [...] then of course they're going to come into the classroom in a disposition where they're already on the offensive. So, that aggravates a cycle, so then that kid becomes "these kids" because you treat them like "these kids."* (P8, W/2nd)

As these quotes suggest, each data entry on ClassDojo embodied teachers' existing prejudices and subjective judgment, which often failed to accurately reflect the being of each student. In practice, the use of ClassDojo reflected and perpetuated the structural bias deeply embedded in education and the broader societies around it.

5.3.2 Reinforcement through Feedback. As mentioned previously, a key affordance of ClassDojo was providing immediate audio and visual feedback to students whenever they perform any behavior deemed desired or undesired. Past HCI researchers believed that behavior management technologies' automatic feedback could ease teachers' burden of juggling between data collection and providing verbal feedback, and consequently provide consistent and reliable feedback to students [70]. These findings might be insightful but incomplete. Our results instead suggest that such automated audiovisual feedback could unintentionally reinforce teachers' existing biases and prejudices in practice.

P15, for example, worked at a public elementary school, and over 70% of her students came from low-income families. She described how she was subconsciously impacted by ClassDojo's visual feedback on students' classifications:

> *If [...] I'm not intentional about how I see and perceive a child and their behavior, then I might have like a negative bias against them. [...] I like the visual example of ClassDojo and I'm a very visual person, but when I have that presented on a screen, I'm subconsciously taking in that information about my class.* (P15, W/5th)

Confirmation bias theory reminds us that people tend to choose information to support and confirm what they already believe [62]. As suggested in P15's quote, the biased data collection converted into direct visual feedback that disguised as an "objective" data representation of the student. Teachers then took in this biased data representation as the "objective" reflection of the student, and used it to confirm and justify existing biases, which consequently further entrenching prejudices and stereotypes. In the case of ClassDojo, we argue that the automated immediate feedback mediated and further accelerated confirmation bias.

5.3.3 Institutionalizing Bias. Besides reinforcing personal prejudices, these biased data points could also feed into the broader systematic stereotypes. As mentioned earlier, ClassDojo connected varied stakeholders, including parents and school administrators. Sometimes, teachers would also share their data insights with other educators and staff in the school. In this way, students' already biased behavior data on ClassDojo could be communicated with actors who had access to the system, which institutionalize certain biases against particular norms, values, and characteristics. As stated by P10, such "*shared bias*" could be powerful in "*shifting the dynamic of how we think about our kids*." P10 described how her co-workers' open discussion on some students past behavior data informed her assumptions of and initial attitudes toward these students:

> *If teachers are sharing that data, it begins to build this shared bias towards these kids. Because it's, "Look at this..." And I just see negative or red check marks. [...] So, my first intention, is towards mitigating any issues, before they even start.* (P10, W/7th-8th)

This quote highlights how the use of ClassDojo could extend existing classroom surveillance and bias to broader socio-technical assemblages. In this way, biased but seemingly "objective" data points served as the messenger among these assemblages, constructing and entrenching shared biased narratives.

5.3.4 Reflecting on Bias. To this end, some teachers highlighted the importance of recognizing their own biases, understanding their own positionality, and constantly reflecting on the potential consequences resulting from their biases. P16 noted:

> *And I would always check myself really for my biases, and looking to see like, "All right. Did the only warnings I gave out this week... Were they only to the Black students in my class, more specifically, the Black boys? What did I give them warnings for?" And I would use that to check myself.* (P16, W/3rd)

In P16's case, she described occasionally reviewing the whole class's daily report and making sure the quiet students do get points from her. P7 told us she would sometimes check her students' Dojo points from other teachers: "*if it's my points that are lacking, [that means] maybe I'm too tough on that kid, maybe I should make some positive interactions with them.*" As these examples suggest, self-reflection was helpful for some teachers to unpack the subjectivity in their use of ClassDojo. Instead of seeing behavior category definition, data collection, and data interpretation all as neutral processes, such critical reflection could serve as the starting point for teachers to think through and mitigate the bias embedded in each step of the classroom surveillance.

5.4 Potential Psychological Impact on Students

Besides reinforcing biases, we emphasize that ever-present Band-Aiding could lead to unintended psychological impacts on the students. Teachers observed that it was common for students to get discouraged, develop an "*I don't care*" attitude, and thus give up in the classroom, if they had been constantly targeted by teachers and the ClassDojo point system. P9, for instance, admitted that some of her students would give up and "*[go] for the low score instead of the high score*" due to their embarrassment and lack of motivation.

This "*I don't care*" attitude resonates what Deci and Ryan described as impersonal motivational orientation in Self Determination Theory [27]. In our case, students might perceive limited control over how their behavior was interpreted by teachers, which could result in their internal frustration and self-denial. In addition, teachers observed that students could internalize the classification and categories generated by teachers and their use of ClassDojo, even at an early age. For example, P14's kindergarten students described themselves and other students as "*the always on 100% kid*" or "a bad boy" in terms of their performance on ClassDojo. At the same time, teachers raised the concern that having constant audio-visual feedback on these classifications could further contribute to the self-fulfillment of "identities" constructed by teachers and other stakeholders. P16 noted:

> *I've had kids self identify as "I'm always participating" or "I'm always not participating." [...] ClassDojo can be used to [...] affirm [these ideas] and perpetuate them even more. So that's partly why [with] that display of green points versus red points subconsciously, a child or teacher can internalize something about that child's "identity," and that gets attached to their name.* (P16, W/3rd)

As indicated in this quote, not only could teachers justify and confirm their biases through ClassDojo's immediate feedback, students could align themselves and their peers with biased technology outputs. On top of self-fulfilling biased labels, our participants observed that students might grasp and internalize the sense of being unfairly targeted and treated. P10 told us that she had students accusing other teachers of misinterpreting their behavior or work ethic, saying things like, "*[S]he'll never put [...] points down when I do my work, she'll only put points down when I'm not doing my work*" or "*he doesn't ever give me any credit for when I do get to class on time.*" She continued and unpacked the potential long-term effect resulting from such biased surveillance:

> *If a kid hears for so long, "You're bad. You're not good at this," all these things, they begin to believe those things. If multiple people treat them a certain way over the course of years, especially the development years, that's how they begin to feel. And then, thus, they begin to act.* (P10, W/7th-8th)

Brought together, these quotes and cases revealed that the socially constructed logic of classroom surveillance could in turn serve to construct the negative psychological and social outcomes for students who have already been disadvantaged in different ways. This raised the broader concern of the long-term psycho-social influence on these children—through this lens of being targeted by institutional biases, how would they view themselves, and, how would they view the world going forward?

6 DISCUSSION

Technology is neither separate nor independent from society; it is both socially constructed and socially constructing. At a higher level, our work illustrates how behavior management technologies, together with their surveillance logic, embody the entanglement between the social and the technical. Through an interview study with K-8 teachers, we drew attention to the unintended consequences of the use of ClassDojo, one of the most popular data-driven behavior management technologies on the market. In particular, our results have shown that the use of ClassDojo decontextualized the complex socio-emotional underpinnings of student behaviors and reduced the complicated relations among teachers and students to the management of coded student behavior data. We also illustrated how the data collection and interpretation processes embodied teachers' existing prejudices, and biased data entries were then used to justify and confirm their prejudices. Together, our results reveal how bias was coded in each step of classroom surveillance, and how the use of behavior management technologies could reinforce certain prejudices and privilege certain types of actions, norms, values, and states of being in the education setting.

Situating our work in past literature within HCI and adjacent fields, we synthesize our findings and discuss how classroom surveillance mediated by the use of behavior management technologies amplifies existing disadvantage and inequality in education. We conclude by drawing from Lindtner et al.'s reflexive-interventionist approach [51], to propose concrete considerations for future HCI researchers and practitioners to both avoid pitfalls and anticipate alternative futures of educational technologies that are worth pursuing going forward.

6.1 Exacerbating Inequality in Education

Two salient themes in our findings are profiled students and reinforced bias in practice. Oscar Gandy's notion of "cumulative disadvantage" reminds us of how surveillance technologies contribute to social inequalities in practice [38]. Such technologies further push disadvantaged people and communities to the margins of society, and "condemn many of them to a life of extreme relative deprivation" [38, p.12]. Our results suggest that the intention of doing what is "good" and "right" for students through educational techno-solutions could in fact materialize and perpetuate unequal conditions of marginality in two ways: (1) exposing disadvantaged students to differential and augmented scrutiny, and (2) potentially reinforcing biased identity labels and respective feedback.

Aligning with past findings on teacher biases, our analysis indicates that some teachers heighten their surveillance over certain students based on racialized and gendered classifications [65, 72], labels of dis/abilities [61], parental backgrounds, and more. Consider that some teachers acknowledged they expected students with certain characteristics to behave in particular ways and were actively ready to penalize these presupposed behaviors. The point system and universal behavioral parameters limited and directed teachers' attention to what they defined as "problematic" and deviations from the normal, such as "talking out of turn" or "not staying in seat." In effect, teachers could be biased towards certain behaviors and not others, and some student behaviors become hypervisible under surveillance. Moreover, the desired behaviors defined by ClassDojo and teachers—for example, "being respectful"—are seemingly universal hence "objective." However, what "respectful" means, according to our participants, is culturally and racially defined (per P4 and P10). To this end, we argue that certain dominant classroom orders and norms could be reproduced and engineered in the process of data collection (e.g., seeing "being respectful" defined in white normative terms as desirable), and certain behaviors performed by children from underrepresented groups could continue to be discouraged and stigmatized, and lead to potential exclusion from educational resources and services (per P6 and P17).

Although our investigation did not include the children's perspectives, when situated with past research, our results suggest that the data-driven classroom surveillance on students' embodied behavior could potentially lead to negative psychological impacts and social outcomes, such as a growing sense of resignation, stress [71], and shame [84]. In her now-classic book *Dark Matters*, Simone Browne's notion of "digital epidermalization" cautions us that surveillance mechanisms often construct the "truth" and "identities" of disadvantaged bodies at the expense of individuals' voices and interests [16]. In our case, we see how student behavior data that embody teachers' biases are in turn viewed as the "truth" to confirm and reinforce the status quo. On the students' side, our participants believed that students could align themselves with these constructed "truths" and "identities." Therefore, the"truth" and "identities" that embody the biases and systematic inequalities could produce meanings about both who the students are and the meaning through which they understand themselves and view the world.

In the meantime, it is important to caution that teachers can uncritically associate student behavior to particular kinds of home environments or socioeconomic traits, as we depicted in our findings. This could naturalize the locus of marginalized students' distress at family and community levels. As such, students' distress resulting from attempts to meet dominant social norms and normative behavior expectations can be negatively attributed to families and communities. This has a disproportionate impact among marginalized groups, or those who have long been scrutinized by the interlocking oppressive systems of racism, classism, and xenophobia [59]. Propagating this insensitive rhetoric risks overlooking the situated lived experience and subjectivity of each student which can in turn legitimize dominant discourses that constructed such rhetoric originally [2, 14].

In addition, our work suggests that educational technologies like ClassDojo could disseminate and perpetuate biases against certain students or certain groups of students in the broader socio-technical assemblages. Contingency accompanying the questions of *what to measure*, *who to measure*, and *how to measure* could accumulate and escalate the everyday politics and bias in the classroom to the institutional level. These observations lead to further reflections on the broader issues related to the justice and equity of data use in future educational technology design and use. Accordingly, questions arise: how long will the biased intimate behavior data be stored? How will such data be processed and used in the future? How will such data reconfigure the education system and impact the school-to-prison pipeline? And once this data is made available, what are the underlying risks of these biased data connecting with other data-driven systems such as insurance, social welfare, employment, policing? While these questions are beyond the scope of this current paper, we must continue to reflect upon them critically, and future research should further investigate.

Taken together, our case study of ClassDojo foregrounds how the use of data-driven technologies could mediate and amplify the interlocked matrices of oppression and assumptions based on race, gender, ability, culture, and more, combined [32, 64]. That said, we attempt to problematize the uncritical design and use of data-driven technologies in the education setting in our field. Past HCI research has endorsed data-driven educational techno-solutions like sensing and automating tools as they are able to collect "objective measures of behavior" [56, p.5]. We argue that such technosolutionist view essentially overlooks human subjectivity and bias embedded in the use of these technologies, as shown in our analysis. Future HCI researchers and practitioners must think critically about the potential socio-technical consequences that systems can unfold in practice when designing educational technologies and data-driven systems in general. As Ruha Benjamin's quote, cited at the beginning of this paper, suggests [11], lack of intention to harm should not be used as an alibi for designing new seemingly neutral technologies without attending to their contingent unfolding in the everyday reality.

6.2 Considerations for Designing Future Educational Technologies

Yet, the technosolutionist perspective still dominates the design and implementation of data-driven technologies today [46, 51]. This perspective uncritically advocates technologies as the solution to address complex societal challenges like education and health. In this light, we turn to Lindtner et al.'s reflexive-interventionist stance to investigate how the HCI community and future educational technology designers and practitioners can simultaneously avoid the pitfalls and negative effects as identified in our "*critique of the present*" and employ an "*anticipatory design*" approach to speculate an alternative future (cf. [51]). Accordingly, we propose three interventions and considerations as a first step for designing and using future educational technologies: 1) providing context, 2) exposing bias, and 3) speculating the alternative normal.

6.2.1 Providing Context. Data are not value-neutral. As D'lgnazio and Klein noted, recognizing and considering the social relations and contexts in which data are produced and embedded is critical for collecting and making use of the data [28]. Our work has shown that ClassDojo behavior data fail to take contextual socio-emotional underpinnings and the nuance of behavior into account, and recall from P15 that ClassDojo data only record whether or not a pre-defined behavior parameter is met or not. For future educational technology, there must be space for incorporating nuances and contextual information in the data collection process, including who is doing the collection work, how the behavior data is collected, and the environment in which the behavior data is generated and collected. Indeed, such data are still subjective, yet accurately recording the context would increase transparency in future use and allow for analysis of unequal power relations inherent in the data [11].

More importantly, future designs should enable the communication of context when presenting and making use of data collected from students. As suggested by Hetey and Eberhardt, numbers do not speak for themselves [44]. When communicating data and data-informed decisions, future HCI research and design should carefully attend to how to make visible the nuances of the data point itself and the social dynamics that informed the data point. Unlike color-coding and universally quantifying each student as in ClassDojo, to contextualize is to convey that any student behavior and performance does not result from stereotypes or biases [44]. Research in education has long shown the discipline gap along racial and socioeconomic lines is in part resulted from the cultural mismatch between teachers and students [19, 26, 60] and broader power structure in which such disparities are engineered [52]. Yet, without explicitly conveying such background and the context in which the data was collected, student behavior data and data-informed decisions (such as ClassDojo immediate audiovisual feedback) can be misused to justify teachers' existing bias and stereotypes (e.g., Black and brown boys are more disruptive in classrooms (per P6, P8 and P10)).

6.2.2 Exposing Bias. While we have shown that the use of ClassDojo could consciously and subconsciously reinforce teachers' biases, our results also reveal opportunities for systems like ClassDojo to support teachers' self-assessment of their own biases. Recall that P16 checked her class's weekly report to reflect on whether she disproportionately scrutinized Black boys; P7 similarly used the class weekly report to reflect if certain students were ignored.

While the data collected on students are currently utilized to evaluate student behavior and performance as well as predicting learning outcomes [56], future educational technology should shift the power dynamic by exposing and making visible potential biases in the collected data. For example, is a student being constantly profiled? Are students with certain shared traits constantly receiving more undesired behavior warnings? And is the student getting more rewards from one teacher but more warnings from another teacher? This shift will allow data-driven educational technologies to raise teachers' awareness of their biases and nudge them to reflect on the negative consequences they have on their pedagogy and interaction with students. Aligning with Ogan's call [63], instead of using data-driven educational technologies as the device to evaluate and define students, we should leverage them as an anchor to hold teachers and other stakeholders accountable and support their reflexivity. A similar approach has shown effective in making visible the racial disparities and overt bias in policing services for the purposes of shifting policing culture and supporting police-community relationships [43].

Critical design and social justice-oriented design in HCI have long been stressing the importance of researchers' and designers' commitment to reflexivity in practice (e.g., [8, 9, 29, 32, 34, 35]). We extend this call and argue that it is also crucial to design for supporting *users' reflexivity* in order to achieve socially just and equitable outcomes. This way, users could start reflecting on what power dynamics and assumptions they are bringing into the use of technologies, and socio-technical consequences that their practices may unfold. To this end, we can also view making visible bias as a manifestation of what Kaziunas et al. suggested as *caring-through-data* which emphasizes that the flexibility of making space for multiple ways of being through/with/in data [46]. For example, our paper discussed how visual feedback and reports on student behavior could reinforce teachers' biases. Instead, we could design for a different type of feedback—one that indicates a variety of potential factors that lead to the behavior, a variety of options to engage with students and make sense of the behavior, and importantly, the potential biases associated with the behavior and the data point.

6.2.3 Speculating the Alternative Normal. Essentially, our work illustrates a case where technology reproduces and amplifies the existing social order and dynamic in which it was designed and used [73]. Dominant norms and beliefs are used to define and create educational technologies like ClassDojo and the logic of classroom surveillance. To this end, instead of designing within this default setting, future educational technology researchers and practitioners should challenge the status quo and dismantle the default normal in the classroom [11]. Following the reflexive-interventionist call for speculatively imagining alternative futures [51], future design should center the values and everyday realities left out of the current educational technologies, allowing a way of imagining marginalized student lives beyond the existing logic of classroom surveillance. For example, Harrington and Dillahunt's recent work provides an example of speculative co-design with Black young adults as an effective method to conceptualize and envision a more equitable individual and community future [41]. This participatory speculative method can effectively make space for problematizing the undergirding bias and denaturalizing the assumptions of "who gets to future" in education [74].

Taking this further, we argue that the HCI community should reflect critically on the presupposition that designing single pieces of Band-Aid technologies is the normal. Angela Davis, an African American philosopher and political activist argues that the U.S. prison system is not an isolated system; rather, it is situated in a complex network with human and non-human actors of correctional communities, healthcare workers, transnational corporations, policymakers, courts, and more [25]. This networked perspective stresses that there is no *single* replacement of the prison and punishment system that can fundamentally address the systematic oppression embedded within. Instead, thinking about the alternatives requires us to focus on the network of actors around the system, and reconfigure the varied forms of domination and oppression (e.g., racism, class bias, sexism, etc.) embedded in each actor and the assemblage of power relations among them. In our case, ClassDojo becomes a Band-Aid because it attempts to serve as the single direct replacement of classroom behavior management and classroom surveillance system while ignoring the broader network.

As such, future HCI research and design should move beyond myopically Band-Aiding student behavior through new single pieces of educational technologies that replicate and automate the unjust logic of classroom surveillance and behavior management. Instead, we must question and challenge the naturalization of deploying surveillance and behavior management systems in classrooms and schools. Collectively, we should redirect our focus onto envisioning a set of alternatives to reconfigure and support the power relations that uplift children, be it technology or not. For example, we should consider, instead, how to better balance the education resource distribution such that students—especially those who are already underserved—would have more access to services and resources like professional social workers and psychologists in and beyond schools.

7 LIMITATIONS AND FUTURE WORK

Our study has three limitations. First, our sample was U.S.-centric and we recruited 20 participants recruited through online advertisements (i.e., Reddit and Facebook) and snowball sampling, which could lead to self-selection bias in our study. Although our participant sample included people from various backgrounds, the experiences of ClassDojo users in different education systems and and those who did not volunteer to participate in the interview may vary. Future work can examine differences in teachers' perceptions and experiences across regions. Additionally, while teachers were the main focus of this paper, we acknowledge students' experience under classroom surveillance and engagement with ClassDojo is a study unto itself. Specifically, as noted earlier, future work can involve speculative co-design with students to contest the very notion of behavior management as a natural site of technology deployment in classrooms. Second, our interview study is qualitative in nature. Due to the Covid-19 lockdown, we were not able to conduct in-person field work, and future studies can take on an ethnographic approach in classrooms to unpack the dynamic, subtle, and transient uses of ClassDojo. Future work can also validate our findings and assess the specific effects of classroom surveillance through quantitative methods. Finally, even though we stressed confidentiality and ensured teachers that there were no right or wrong answers before interviews, teachers might have answered our questions in a way that they considered "more socially desirable" [40, p.1], which could result in social desirability bias in our findings.

8 CONCLUSION

In this paper, we presented a qualitative inquiry about the unintended socio-technical consequences resulting from the use of a data-driven behavior management technology that mediates the logic of surveillance on student embodied conduct in the classroom. Through the case study of ClassDojo, we have identified four nuanced ways in which the use of data-driven surveillance technologies could materialize and perpetuate unequal conditions of marginality: 1) simplifying the complex socio-emotional, cultural, and historical underpinnings of data points, 2) reducing and overlooking human-to-human engagement, 3) replicating, reinforcing, and institutionalizing existing biases and stereotypes, and 4) causing potential negative psychological and social outcomes on already disadvantaged individuals under surveillance. While this work focuses on data-driven surveillance in classrooms, future research can investigate if these aforementioned socio-technical consequences apply to other surveillance sites and contexts. Based on our findings, we proposed three considerations as a starting point for HCI and educational technology designers and practitioners to pursue more socially just and equitable outcomes in education going forward: 1) providing context in the collection and communication of student data, 2) exposing teacher bias and supporting users' reflexivity, and 3) speculating the new normal within and about educational technology.

In conclusion, the goal of this paper is to call for critical reflection on seeing classrooms and schools as natural sites to deploy new data-driven educational technologies and behavior management systems. We aim to initiate a humble reflection on the ways in which education, technologies, and embodied human actors have been thought, acted, and entangled upon.

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