# Probing Actionability in Learning Analytics: The Role of Routines, Timing, and Pathways

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## ABSTRACT

Actionability is a critical, but understudied, issue in learning analytics for driving impact on learning. This study investigated access and action-taking of 91 students in an online undergraduate statistics course who received analytics designed for actionability twice a week for five weeks in the semester. Findings showed high levels of access, but little direct action through the provided links. The major contribution of the study was the identification of unexpected indirect actions taken by students in response to the analytics which requires us to think (and look for evidence of impact) more broadly than has been done previously. The study also found that integrating analytics into existing learning tools and routines can increase access rates to the analytics, but may not guarantee meaningful engagement without better strategies to manage analytic timing. Together, this study advances an understanding of analytic actionability, calling for a broader examination of both direct and indirect actions within a larger learning ecosystem.

## CCS CONCEPTS

• **Applied Computing**; • **Education**; • **Interactive learning environments**;

## KEYWORDS

Actionability, learning analytics implementation, data-informed learning, formative feedback

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## 1 INTRODUCTION

Learning analytics leverage data about student learning processes with the goal of improving them as a route to better educational outcomes [19]. Historically, the information generated has not been offered to students directly but has been mediated by educators who use it to inform instructional modifications and institutional decision-making. Recently, however, the situation has changed, with greater attention given to the importance of, need for, and creation of student-facing analytics [20]. This shift aligns with the ethical position that students, as both the primary source of data and the main beneficiaries of its use, should be more involved in analytical processes [17, 20]. The result is a growing interest toward, and research about, analytics designed for student use, leading not both tool development and also increased implementation [1].

More recently, studies have expanded beyond tool development and lab testing to probe how students work with analytics to support their learning in real-world settings (e.g., [3, 11]). Examination of students' actual use of analytics in practice can provide critical input for building and implementing impactful student-facing analytics as it is well-established that simple exposure to learning data does not necessarily lead to actionable insights [1]. Results to date are sobering: studies examining the use of student analytics reported great variation in the percentage of students who ever even looked at the analytics, ranging from a max of 90% to a low of 52% [3, 7, 9]. Even in cases where most students accessed the analytics at least once, duration of use fluctuated, often remaining relatively short, with few students continuing to use analytics to support their learning after initial access [7, 18]. These results raise important issues for research and practice. On the research side, they question the mechanism of successful student learning analytics implementations with the paradoxical findings that despite the sporadic access reported above, there is good evidence that analytics are effective at increasing student performance [12, 16]. On the practical side, the limited access reported makes the usefulness and economic sustainability of analytics use in actual learning contexts also debatable.

Despite the relative paucity of empirical studies unpacking how and why limited analytics use happens, the available evidence does suggest that students' low and varying use of analytics may relate to what analytics are designed and their provision in relation to the characteristics of the local context [3, 7]. For example, [7] reported that analytics use occurred mainly at two major peaks corresponding with midterm and final exams, as well as key points for other assignments. More importantly, it is commonly reported that students decide not to keep using analytics due to difficulty in understanding what to do for their learning based on the information provided [11]. Even when they engage in successful sense-making of the data provided, students encounter challenges and report frustration in deciding what to do next based on these interpretations [11]. Other research has shown that enacting action in response to analytics can be difficult, even when students are able to identify which part of their learning practices they need to change and set the goals to achieve this change [23]. It is also important to note


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that students are not always able to change their behaviors and strategies in line with their intentions and inadvertent changes have also been identified in the literature [9, 23] resulting either indirectly from students' interactions or misunderstanding of the analytics [11].

While the difficulties were commonly reported in taking action in response to analytic sensemaking, some studies have found evidence that students can work over time to adjust their learning strategies and/or enhance engagement based on the analytics. [23] reported that through multiple cycles of reflective practice (action, analytics, reflection) students were able to make and sustain changes in how they engaged in online discussions, for example reading existing posts more thoroughly before replying, and self-monitoring the length of their comments to be more succinct and not overwhelm others. Encouraged by these results as well as growing attention to human-centered learning analytics [2], some researchers have begun to explore how to take actionability into account in the design of learning analytics tools. For example, [4] delineated comprehensive guidelines outlining critical principles for actionable analytics design, including "agentic positioning of stakeholders," "integration of the learning design cycle and design," and "guidance from educational theory". While these initiatives are valuable from a designers' perspective, they have not prominently addressed students' perspectives nor concretized specific design components for actionability; rather, they focused on establishing overarching guidance for structuring the design process. There is also limited understanding of how such design structures impact resulting products and are received by students in practice.

The current paper addresses these gaps by reporting how students consider and act on analytics designed with their input and actionability in mind. The examination of practices of student analytics use focuses on two main aspects: (1) students' accessing of analytics (2) the kinds of actions that students take (or not) in response. This study offers detailed accounts of how students engage with analytics as part of their learning routines, and how they do and do not incorporate analytics-informed insights and actions into their work on learning tasks. The study contributes knowledge about learning analytics actionability within real-world learning contexts and provides concrete implications for tool design and implementation strategies.

# 2 LEARNING CONTEXT & ANALYTIC TOOL

## 2.1 Collaborative Annotation as a Site for Learning

Understanding the learning context is crucial for analytics design and implementation [20]. This study is constructed in the context of collaborative annotation—an educational activity where students and instructors jointly read, highlight, and comment on the relevant sections of learning materials [14]. Effective collaborative annotation relies on students' routines, not just consuming the shared materials, but taking action to respond to them and co-develop ideas with peers [24]. However, this potential is not always realized, due to issues such as inconsistent engagement, low-quality annotations, and hesitation in tool usage [5]. These issues manifest in students' tendencies to focus on irrelevant details, produce repetitive annotations, and accept information uncritically [5, 14]. Such challenges often arise from students' difficulties in interacting with relevant information and identifying which parts of the materials to respond to and how to engage [14, 24]. Student-facing analytics offer an exciting opportunity to address these challenges by providing students with relevant information and helping them become more attentive, critical, and reflective in their tasks [24]. In pursuit of this expectation, the larger project of which this study was a part initially focused on identifying the most pressing need for analytics of collaborative annotation through a human-centered design process. Consequently, the analytic tool was developed with the primary objective of meeting the need for timely guidance in identifying areas for meaningful contributions to the collaborative annotation activities.

## 2.2 Learning Analytics Tool: EntryPoint Analytics

The analytic tool used in this study provides students with individualized analytic-driven suggestions about where they could contribute to their collaborative annotation task (e.g., "Buzz! Check out this active conversation" or "Do you have something to say about the question?"; see Figure 1). This tool was developed through an extensive human-centered design process, engaging 19 students and 3 instructors as co-designers through 4 rounds of workshops and consultations in which multiple decisions were made with the goal of actionability in mind; three tool features are focused on in this paper.

***Incorporate analytics directly into already-used learning tools***: One feature of the product is its use of email as an already used learning tool to deliver individualized suggestions, rather than relying on a separate dashboard typically employed for analytical tools [1]. This decision was prompted by student learning routines and preferences identified in the human-centered design process. Students described that if they had to go somewhere new to view the analytic information, they would not use it and maybe even forget about it. While email is a basic communication tool, students indicated a preference for receiving analytics this way as it would put the info in front of their eyes (they had a habit of checking emails regularly) on the tool they used for collaborative annotation (laptop, not mobile phone).

***Provide direct paths to action from the analytics:*** Another feature was to offer direct paths for students to take action from the analytics. This was expected to address the common challenges in deciding what steps to take after reviewing the analytics [15]. Two different clickable pathways were embedded to facilitate students' seamless transition from the analytics to their learning tasks: (1) through the original reading text suggested to comment on and (2) via the existing annotations suggested to respond to. Through pilot-testing, these design concepts became integrated into the analytic product as the buttons (e.g., "View reading", "View conversation") for direct access to the relevant reading and conversation sections with a single click.

***Align timing of the analytics with the timing of the learning activities:*** Two strategic time points were chosen for analytics delivery: once early in the week and once towards the end of the week in relation to the course's weekly schedule. This decision


**Figure 1: The EntryPoint Analytics**

was made to avoid overwhelming students with frequent notifications, while considering students' comments expressed during the human-centered design process that their responses to the analytics would differ depending on when they were in their weekly learning routines and if they had already started to participate in the collaborative annotation activity or not. Therefore, four different versions of analytics were delivered based on (1) if the analytics were being provided early or late in the week and (2) if the student had already participated or not.

- **Version "Early/Not"**: an email sent early in the week for those who have not yet participated served as a motivator/reminder
- **Version "Early/Started"**: an email sent early in the week for those who started participating served as a motivator/review
- **Version "Late/Not"**: an email sent late in the week for those who have not yet participated served as a reminder
- **Version "Late/Done"**: an email sent late in the week for those who participated served as a review/class preparation aid

## 3 METHODS

This work studied student use of the EntryPoint Analytics designed for actionability in the context of 5-week implementation in an online undergraduate statistics course with respect to three questions:

1. How do students access the analytics?
2. How do students take action on the analytics?
3. What factors impact students' perceived actionability of the analytics?

### 3.1 Course Context, Participants and Analytics Delivery

The EntryPoint Analytics were implemented in a large fully asynchronous online undergraduate course on statistics in Spring 2023. Students were asked to use Persuall, a collaborative annotation tool, to read, annotate, and discuss assigned materials on a weekly basis. Each week, students were given one to three reading materials and required to make at least two comments on each by Friday midnight. While the Perusall activity accounted for 8% of their final score, this course asked students to iteratively read, post, discuss, and revisit to prepare for class lectures and complete other learning tasks such as quizzes and essays. Thus, analytics and assignment had continued value throughout the week. 91 students registered in the course received the analytics as a regular learning tool twice a week from the third to seventh week of the semester (5 weeks total). Students received different versions of the analytics depending on their participation status (whether they had started participating in the learning task or not) and the time of the week (early or late). Participation status was measured one hour prior to the distribution of the analytics. 15 students indicated willingness to participate in a post-implementation interview, and 10 students were finally selected for interviews using stratified sampling to ensure the diversity of learning routines: 6 who started working early in the week and 4 who did their work close to the deadline. The sample included 2 self-identified males and 8 females, 3 international students, and 1 first-generation student.

### 3.2 Data Collection & Analysis

**Analytic Access and Click-throughs:** Data about student access to the analytics was collected through the same tool used to deliver the analytics. This data provided tracking of who accessed the email including the analytics, when, how often, and the extent of their button clicks.

**Interviews:** This study used a well-established think-aloud protocol for interviews, asking students to walk through the specifics of their analytics use related to each of the three research questions about learning analytics access, actions, and perceptions. The interview was conducted via supervised video-conference sessions, a technique to carry out in-depth examination and collection of analytics use from screen and video recordings, think-aloud protocols, and debriefing/reflection questions [10]. During the interview, students were asked to open one of the analytic emails and describe their typical interaction with it. Students were asked about their access patterns (e.g., when and why they usually accessed the analytics), actions taken (whether they took action, what actions they took, and how), and their perceptions about the actionability of the analytics. To specify their answers, they were requested to point to certain parts of the analytics on the screen while thinking aloud. Interview responses were analyzed using affinity diagramming as a qualitative inductive coding method [6]. Following previous studies on the use of analytics in supervised sessions [10, 22], this approach was chosen to help identify important categories, their meanings, and underlying factors. In alignment with the research questions, three main areas were examined: student access of analytics, clicking the buttons in the analytics, and any other action-taking. The process began with line-by-line readings of all transcripts with use of screen captures as needed to identify any responses relevant to these three areas. This process was repeated for all the interview transcripts, resulting in a comprehensive list of relevant ideas. Ideas for each area were then consolidated into a hierarchical structure of categories based on similarity, through multiple rounds of integrating comparable ideas and removing less substantiated ones. The primary researcher took the initiative for each step of the analysis, consulting and revising ideas and categories in each phase through several rounds of discussions with the other researcher.

# 4 FINDINGS

## 4.1 How Do Students Access the Analytics?

The vast majority of students opened the analytics upon receiving them (see Table 1). Among those who had not yet started their work in Perusall at the time of analytics delivery, the open rate for the first delivery was 94%, and it remained between 84% and 88% up until the second-to-last delivery. The open rate for the final analytics delivery was only 62% but this is partially attributed to spring break starting at the end of this week. For students who had already made at least one comment in Perusall when they received the analytics, the open rate was 100% for the first delivery. While only 77% of students opened the analytics later in that week, their open rate remained consistently high, ranging between 81% to 95% over the next four weeks. Only 3 students chose to opt out of receiving the analytics over the implementation. In terms of access patterns, most students accessed the analytics within an hour of receiving them and this trend was stable across weeks and versions of the analytics. With the exception of one student who accessed the analytics exclusively on their mobile device, all other students primarily used desktop or laptop computers. These findings from the log-file data were corroborated by the interview data. Most (8 of 10) students reported a habitual tendency to open any received email promptly: "*I opened pretty much all of my emails and read. I've definitely opened all of them (the emails with the analytics) because that's just how I am as a person* (Stu 9)." These 8 students explained that when they accessed the analytics they generally then skimmed through the information. The two remaining students (Stu 2, 10) indicated rare access of the analytics, stating that while they may have opened the analytics as part of checking their emails, they did not look through the content.

For the timing of their analytics use, 6 of the 8 students who described looking through the analytics tended to do so later in the week, either while performing the learning task (Stu 1, 4, 8) or after completing it (Stu 3, 6, 7). One student (Stu 9) described using the analytics early in the week while engaged in the learning task and another (Stu 1) did not specify a specific time frame. Looking across the five weeks, two students (Stu 3, 6) mentioned greater use of analytics at the start of term, in part due to their unfamiliarity with Perusall. Two students (Stu 7, 8) described using analytics frequently when facing challenges with their learning tasks, while one student (Stu 9) expressed a decrease in their frequency of use over time as they were annoyed to receive a reminder of the work. Three students (Stu 1, 4, 5) stated no changes over time.

## 4.2 How Do Students Take Action?

Eight students reported taking specific actions related to their reading and commenting activities within the collaborative annotation platform in response to the analytics. These actions were taken either ***directly*** by clicking on the buttons / hyperlinks embedded in the analytics or ***indirectly*** during a visit to the learning task, not specifically prompted by the analytics.

*4.2.1 Direct Paths to Actions .* While students' access (open) rate of the analytic email was high, the click-through rate was low (see Table 2). Over all 5 weeks, only 19 of the 91 students clicked on the links provided in the analytics to directly access the learning task; only two students clicked more than once in a week. Notably, students who had not yet started participating in the learning task were more likely to click on analytics than those who had already participated. Their click rate was relatively high in Week 3, the first week of implementation (see Table 2). Particularly, most of the clicks from these students were on the "Buzz! Check out this active conversation" metric which highlighted a part of the reading that had many accompanying comments. This aligns with a kind of use described in the interviews, where several students expressed a tendency to use the analytics as a preview to get a prospective idea of what is going to happen in the learning task before diving into it: "*It was just part of my routine now, like "Let me see what people are looking at and saying right now?" And get a glimpse into the discussion before I actually open it up. It's like when you dip your toe into a pool to see how cold or warm it is. It's giving me a preview of how the notes are for this week* (Stu 9)."

*4.2.2 Indirect Paths to Action.* In contrast to the low click rates for the direct paths to action embedded in the analytics, the interview analysis revealed that eight of the ten students expressed a tendency to use the analytics even without clicking the buttons. Instead, they described taking specific actions in the learning task in response to the analytics when they visited Perusall: "*I haven't clicked on the "view reading" and gone straight from there. If I [open] the email, I'll just look through it, and then see "oh, these are the kinds of comments that people are making. And then whenever I decide to go back to Perusall, I'll just use what I remember from the emails* (Stu 7)."

The most common actions that those students took based on the analytics were revisiting and rereading certain parts of the readings that were suggested by the analytics (Stu 5, 6, 7, 8, 9): "*One thing that [the analytics] definitely inspires me is to go and open the website and look through the textbook* (Stu 7)." When rereading, some students (Stu 5, 8) tried to extract the main ideas by skimming the sections: "*I'm just going to click on this and see what other people wrote here and then go through each section. I feel like I can get the main ideas or the main points from this paragraph without having to read the whole thing* (Stu 8)." Other students focused on complex aspects of the readings that might require additional attention: "*When I realized that there were some technical terms in there [analytics] people were talking about. So, someone was seemingly struggling or trying to figure out the topic. It called me to immediately start working on it and figure it out, because I know statistics, and data and probability are a little bit harder* (Stu 9)." When rereading the sections, several students (Stu 7, 8, 9) focused primarily on the act of reading itself, rather than immediately responding to the comments:

**Table 1: Student Access Rate to Analytics across Weeks**

| | Week 3 | | Week 4 | | Week 5 | | Week 6 | | Week 7 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Early** | **Late** | **Early** | **Late** | **Early** | **Late** | **Early** | **Late** | **Early** | **Late** |
| **Not yet participated in learning task** | 80 / 85 (94%) | 42 / 48 (88%) | 63 / 71 (89%) | 41 / 47 (87%) | 62 / 72 (86%) | 41 / 48 (85%) | 57 / 67 (85%) | 41 / 49 (85%) | 57 / 68 (84%) | 34 / 55 (62%) |
| **Already participated in learning task** | 6 / 6 (100%) | 33 / 43 (77%) | 18 / 20 (90%) | 36 / 43 (84%) | 16 / 18 (89%) | 34 / 42 (81%) | 19 / 23 (83%) | 38 / 40 (95%) | 17 / 20 (85%) | 35 / 43 (81%) |
| **Total Students** | **91** | **91** | **91** | **90*** | **90*** | **90*** | **90*** | **89*** | **88*** | **88*** |

* *Changes due to student(s) who chose to opt out*

**Table 2: Student Click Rate to Analytics across Weeks**

| | Week 3 | | Week 4 | | Week 5 | | Week 6 | | Week 7 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Early** | **Late** | **Early** | **Late** | **Early** | **Late** | **Early** | **Late** | **Early** | **Late** |
| **Not yet participated in learning task** | 5 students 25 clicks | 5 students 20 clicks | 1 student 3 clicks | 1 student 3 clicks | - | 3 students 6 clicks | 1 student 3 clicks | 2 students 9 clicks | 1 student 3 clicks | 2 students 6 clicks |
| **Already participated in learning task** | - | 1 student 3 clicks | 1 student 3 clicks | - | - | 1 student 3 clicks | 1 student 3 clicks | - | - | 2 students 19 clicks |

"*If I go back to page one and read through everything again, I'm going to be more focused on whatever I'm reading, rather than trying to think of a response in response to the question* (Stu 8)." Instead, this reviewing activity helped them generate their own thoughts about the readings before formulating a response: "*I need to go through the textbook on my own. Then I just use that [suggested] question as a little piece of background to help me come up with my own questions or use other people's comments to do that. I think it is something that gets me started thinking about it* (Stu 7)." Importantly, several students (Stu 3, 5, 7, 8, 9) reported experiencing implicit effects of the analytics, such as increased awareness of the suggested parts when reading the task: "[*The analytics are] helpful to see what other people have found interesting. Then I might be more aware and keep that in mind in it, knowing that it's a section that has been noted a lot* (Stu 3)."

Another frequently reported action (Stu 1, 4, 5, 6, 7, 9) was using the analytics as a starting point to respond to the existing conversations: "*When it highlights someone else's question they have, it makes me more inclined to want to answer it. I've also seen questions that I've been like, "oh, I know the answer to that", and I've gotten back in and answered that* (Stu 6)." This further helped them revisit the conversations and decide what responses they would make: "*The question ones are the most helpful because it would give me an incentive to go into the textbook and look at what the person commented. Then I read this section to see "oh, either I will have a follow-up question, upvote, or give that person an answer"* (Stu 7)."

## 4.3 What Factors Impact Students' Perceived Actionability?

Several students (Stu 1, 2, 3, 7, 8) encountered difficulties when attempting to take action in response to the analytics, citing two main reasons. One important reason for perceived low actionability was that the students did not feel that they received the analytics at a time that best aligned with their learning routine. In some cases, students (Stu 1, 3, 8) had already completed the tasks and therefore showed reluctance to revisit again in response to the analytics: "*Because I already completed my responses, I don't really revisit after I completed my work just because I move on to other things* (Stu 3)." In another case, students suggested that responding to the analytics required prior participation: "*Whenever I'm doing the reading, I think this email is probably more effective if you've already done the reading. I feel like if I were to click this, and then I would just get bounced to this question. But just in a footnote on page 18, if I haven't read pages one to 18 yet, it would be really hard for me to answer this question or respond to it well* (Stu 8)." Several students (Stu 1, 2, 10) reported anxiety and irritation in receiving the analytics as a reminder of a task they needed to work on: "*If I have done it [the learning task] on Sunday, then I ignore the email. But sometimes, when I get the email, I think that it means that I haven't done it, even though I know I have. So that makes me a little worried, and I have to go back in and check to make sure I've commented three times* (Stu 2)." Another important challenge in taking action (Stu 1, 2, 3, 4, 7) was a lack of contextual information for the analytics, resulting in difficulties in figuring out what the suggested texts refers to which hindered their confidence in generating relevant comments: "*The only thing that would be a little difficult would be I wouldn't have any context of what the surrounding text is. So even if I did read this comment, I don't know if I'd be able to come up with a response to this person's comment* (Stu 3)." Some students further shared recommendations to provide more context with the highlighted text in the analytics: "*There is no context about this [highlighted text]. So, it will be better to have a brief summary of what are the contexts related to these texts* (Stu 4)."

# 5 DISCUSSIONS & IMPLICATIONS

This study investigated the use and action-taking of the EntryPoint Analytics designed for actionability by 91 students in an online undergraduate statistics course, finding high open rates, low levels of direct action-taking, but evidence supporting valuable indirect actions. While the student worked in a single learning environment with a particular set of tools, the results are valid within this context and speak, at the level of design, to important questions of what we mean by actionability and how we can promote it. Below the findings are discussed with respect to three features designed with actionability in mind: incorporate analytics directly into already-used learning tools; provide direct paths to action; align timing of the analytics with the timing of the learning activities.

## 5.1 Integrating analytics into an already-used tool opens the door to engagement

The results show that most of the students opened the analytics within an hour of receiving them, primarily using computers. This supports the effectiveness of using a tool that students already have integrated into their learning routines to facilitate quick access and potential interaction with the analytics. While access does not guarantee deep engagement, consistent rates above 80% across all five weeks is dramatically higher than anything reported previously in the literature [3, 7, 9, 18]. This underscores the importance of comprehensively discerning students' pre-existing learning routines and patterns during the initial stages of tool development as a way to connect with their subsequent use practices.

## 5.2 The challenge of matching analytic timing with students' learning routines

While students opened their analytics right away, results showed notably low click rates consistently across different email versions, timing and weeks. Interview data suggested that one reason for this was that the time of analytics receipt did not generally coincide with when they normally did annotation tasks. Some students also expressed negative sentiments about receiving analytics through email, perceiving it as a reminder of unfinished learning tasks (see also [11]). Thus, despite finding a tool (email) through which to deliver analytics integrated into students' *overall* learning routines, these findings point to the difficulty of matching analytic timing with the specificity of them engaging in a *particular* learning task. There is a paradox here in that students' proclivity to open communications as soon as they are received meant that the analytics were viewed, but at a suboptimal moment for meaningful engagement with them. This reiterates prior findings that students' use of analytics is not best viewed as an isolated activity, but rather an integral component of their established learning routines in the broader course context [8, 13]. It also highlights the potential of future design work that might shift some of the responsibility for analytic timing from the system to students. Students could be given agency over analytic timing in a variety of ways; for example, through the creation of a "snooze" feature and/or the ability to schedule the timing of one's own analytic delivery [21].

## 5.3 Indirect action as a new route for analytic influence

In this study, embedding the buttons in the analytics as direct paths for action was not well received. However, it turned out that many students found the analytics useful in a broader sense. Rather than clicking on the suggested highlighted parts and buttons, they described ways in which the analytics helped frame their overall approach to the learning task. Several indirect actions reported were directly tied to the information that the analytics provided, including revisiting and rereading certain parts suggested by the analytics using their memory as a guide, and having ideas for comments in mind while reading and seeking quotes from the analytics during reading. As a follow-up to these actions, students added comments to conversations, particularly in response to questions identified by the analytics. These novel findings raise questions about the different routes through which analytics can be considered to be acted upon, and the relative value and traceability of each. For example, while concrete direct actions are easier to identify as analytically-driven, more impactful long-lasting change may come when analytics drive holistic reflection on teaching and learning practices [22]. Future work may delve into this layered actionability of analytics, considering the different modes and timelines through which analytics may lead to changes in learning.

Notably, this study observed a variety of indirect changes made by students prompted by analytics. These changes involved an increased awareness of the suggested parts while reading the task, which influenced their decision-making in contributing to the task. These findings align with previous research [3, 22], showing how people may "keep analytics in mind" for an extended period of time, rather than simply and directly act on them right away. This challenges a traditional conceptualization of analytic actionability, which focuses on direct and immediate behaviors taken [23], potentially failing to capture the full extent of changes that students undergo through engagement with analytics [8]. A broader understanding of actionability requires examining both *direct and indirect* actions that may follow from analytics use that can be collected from course-wide data sources encompassing engagement across various tasks within the course curriculum.

# 6 CONCLUSION

Actionability is critical for learning analytics to have impact in practice, yet has received relatively little attention thus far. This study investigated access and action-taking of 91 students in an online undergraduate statistics course who received analytics designed for actionability, finding high levels of access, but little direct action through the provided links. The major contribution of the study was identification of unexpected indirect actions taken by students in response to the analytics, which requires us to think (and look for evidence of impact) more broadly than has been done previously. The study also found that integrating analytics into existing learning tools and routines can increase access rates to the analytics, but without better strategies to manage analytic timing, this may not translate into meaningful engagement. Together, this study takes a step towards understanding analytic actionability, calling for a broader examination of both direct and indirect actions made from analytics use within a larger learning ecosystem.

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