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Examining Teachers' Professional Learning in an Online Asynchronous System: Personalized Supports for Growth and Engagement in Learning to Teach Statistics and Data Science

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Abstract: Teachers' professional learning often includes online components. This study examined how a case of 37 teachers utilized a specific online asynchronous professional learning platform designed to support teachers' growth in learning to teach statistics and data science in secondary schools in the United States. The platform's features and learning materials were designed based on effective online learning designs, supports for self-guided learning, and research on the teaching and learning of statistics and data science. We paid particular attention to the features we designed into the platform to support self-regulation and personalizing the experiences to meet their preferred learning goals such as allowing for free choice of learning materials, flexibility of when and how long to engage, providing personal recommendations based on user input, internal systems to track progress, and generating certificates of completion. In this study, we used a case study with both quantitative and qualitative data to examine whether teachers had gains in meeting learning goals related to their development in teaching statistics and data science, had sustained engagement, and found the features for personalization supportive for their learning. Results showed, overall, positive growth towards meeting learning goals and making small changes towards improved classroom practice. Most teachers were generally engaged in sustained ways across the study period, though we found six different patterns of completion that highlight ways in which teachers' goal-directed and self-regulated learning occurred within the busy schedules of educators. Several personalized features, especially the recommendations and tracking system, were highly utilized and perceived as supportive of teachers' learning.

Keywords: teacher learning; statistics education; e-learning; recommendation systems; self-regulated learning; online professional development

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1. Introduction

Teachers tend to be lifelong learners, motivated to pursue professional learning that is meaningful to their particular needs. In 2013, Marrongelle and colleagues [1] noted "it is incumbent on the field to capitalize on emerging technologies in the design and delivery of effective professional development" [p. 208]. While the past decade has seen an increase in the development of opportunities for online learning for teachers [2–4] and specifically for personalized learning for mathematics teachers in online spaces [5], more work is needed to provide additional research-based opportunities for educators and to understand the impact of online teacher learning. Our research contributes to how teachers can be supported in self-directed online educational environments in which their learning and changes in teaching practices may be incremental in nature.

The Invigorating Statistics and Data Science Teaching through Professional Learning [InSTEP] professional learning platform aims to support grades 6–12 teachers' professional learning in teaching statistics and data science concepts through personalized online learning. Statistics and data analysis are included in standards for both mathematics and science [6,7], and many states across the U.S. have re-envisioned pathways that include a heavier emphasis on statistics and stand-alone courses on data science [8]. In the U.S., there has been national-level support for this increased focus on statistics and data science through position statements from organizations such as the National Council of Teachers of Mathematics and American Statistical Association [9–11], and reports such as the Statistical Education of Teachers [12] and the PreK-12 Guidelines for Assessment and Instruction for Statistics Education II [13].

Our approach recognizes the busy life of teachers and assumes that learning new ideas and approaches can happen in incremental and personalized ways. This can result in small shifts in preparedness to teach and small changes to teaching practices that have the potential to impact students' learning opportunities related to statistics and data science. Our three research questions are as follows:

RQ1. How does participation in professional learning in the InSTEP online asynchronous platform contribute to teachers' confidence, knowledge of statistics, and professional growth towards learning to teach S&DS?

RQ2. In what ways do participants engage with the learning activities in the InSTEP Platform?

RQ3. In what ways did personalized features support their professional learning in the InSTEP platform?

2. Background and Framing

To aid us in considering how professional learning experiences may have an impact on teachers' beliefs and perspectives, understandings, and practices, we draw upon Mezirow's [14] theory of transformational learning in adult education, which is consistent with constructivist assumptions about learning. Mezirow [14] describes how meaning schemes--comprising of knowledge, expectations, beliefs and perspectives, and feelings --are used by an individual to interpret their experiences, and through reflection on these experiences, may transform their understandings. Peters [15] illustrated how this theory could be used to understand statistics teachers' development of understanding statistics concepts. For example, a teacher might transform her meaning scheme for teaching statistical variation by rejecting a conception that variation is only a measure computed to indicate spread. Transforming meaning schemes often begins with a stimulus, a disorienting dilemma, which requires one to question understandings and beliefs formed from experiences [14]. We intend for materials in the InSTEP learning opportunities to trigger disorienting dilemmas for teachers that can lead to changes in their meaning schemes.

Because the InSTEP platform provides asynchronous learning opportunities for teachers to complete on their own time, self-regulation learning theory is applicable to our work. The process of self-regulated learning involves cognitive, affective, and behavioral components in a continuous process of achievement striving, monitoring, and evaluation that successful learners engage in over time [16]. Adult learners with a stronger sense of self-regulation in their learning are more successful in online learning (e.g., [17]). After an episode of poor performance (e.g., rating themselves low in confidence to teach a statistical idea or encountering a statistics question they are unsure how to answer), a teacher may re-evaluate their learning goals. In contrast, good performance is a sign that progress is being made and their strategy is effective, and this may lead to further goal setting. Specifically in learning to teach statistics, researchers have shown that teachers are motivated to pursue professional learning related to improving their own statistical understandings and confidence to teach as well as learning new teaching strategies for teaching statistics [18]. Others have shown that feedback and positive experiences support teachers' motivation, improved self-efficacy, and are central to maintaining persistence in professional learning related to statistics [19,20].

2.1. Effective Online Professional Learning for Educators

The past 20 years of development of online learning environments has drawn upon the foundational work of Mayer and Moreno [21] about the importance of using multimedia resources to support active engagement. Evidence from past studies specific to teachers' professional learning in online settings shows that focusing on the development of teachers' content understandings and pedagogical content knowledge provides support for learning, promotes active engagement, and addresses varied needs and abilities of participants, which can be effective in changing teachers' instructional practice (e.g., [2,3,22]). Findings from Qian and colleagues [23] led to three recommendations for effective online professional learning: use activities that match teachers' background knowledge and experiences, align activities with curricula, and use motivational design to enhance teachers' engagement. Six design features that emerged from the work of Powell and Bodur [24] include the following: relevancy, authenticity, usefulness, collaboration and interaction, reflection, and context. They also emphasized the importance of learning being job-embedded, meaning teachers should be able to use resources in their job, and that learning opportunities utilize aspects of a teachers' job (e.g., understanding content they need to teach, planning lessons, making sense of students' work, implementing tasks and reflecting on learners' experiences). This aligns with four design principles that informed the design of a collection of Massive Open Online Courses (MOOCs) for Educators offered from an institution in the U.S. that support the following: (a) self-directed learning, (b) peer-supported learning, (c) job-connected learning, and (d) learning from multiple voices [25].

Some members of the author team (Lee and Mojica) designed and implemented three educator-specific MOOCs aimed at developing expertise in teaching statistics using rich data-enabled experiences. Teachers from around the world engaged in these courses and have reported changes in their statistics teaching practices to include larger real datasets and using an investigation process [26,27]. Unequivocally, teachers' confidence to teach statistics drastically increases after engaging in the courses [27]. Many educators did not complete an entire course but instead only engaged in the first 1–2 units (of 5) of a course. Reasons for this pattern of engagement were often that they did not have time to complete a course or were looking for more resources to help learn statistics themselves. Some teachers indicated in follow-up surveys that although they did not finish a course, they learned how teaching statistics involves a cycle and habits of mind and found resources for their classroom that met their needs [28]. Deng and colleagues [29] analyzed patterns of engagement across many MOOCs and classified users in three general categories of engagement: (1) individually engaged users typically enrolled in MOOCs of shorter duration and were highly engaged with completing only a small portion of a course; (2) least-engaged users who also only completed a subset of the course but with mid to low levels of engagement over time; and (3) wholly engaged users who were motivated by the course goals, were highly engaged, and had a high rate of completion. These three patterns are similar to those found by Wiebe and colleagues [30] in MOOCs specifically designed for educators. In their review of MOOCs, Davis and colleagues [4] noted that the designs of typical MOOCs do not account for a learner's past behavior in delivering personalized content, and they suggested that developing and implementing adaptive, personalized systems in MOOCs could make them more adaptable and able to cater instruction based on individual learners. Results such as these led our team to envision a different online professional learning experience for teachers, which led to the InSTEP platform.

2.2. Statistics Teacher Practices, Knowledge, and Beliefs

We know that most mathematics teachers are underprepared to teach statistics and data science concepts and often feel less confident to teach such concepts as compared to other areas of their curriculum (e.g., [31–33]). For over a decade, many researchers have been encouraging opportunities for students to actively engage in real data investigations (e.g., [34,35]). Current recommendations to investigate large data require the use of technology tools throughout an investigative process, such as in preparing, collecting, exploring and visualizing, and summarizing data [36]. While researchers have shown that grades 6–12 students can successfully manage, wrangle, visualize, and model big data sets (e.g., [37,38]), teachers often only utilize tidy, small data sets with students [35], even in AP Statistics courses [39].

Affective constructs such as teachers' beliefs and perspectives about statistics are an important component to building effective statistics and data science teaching practices. These include a teacher's ideas about the nature of statistics, about oneself as a learner of statistics, and about the classroom context and goals for students' learning statistics [20,40]. Experiences learning statistics with a focus on tools and computations may lead teachers to believe statistics is about a set of procedures to produce results or graphs. However, teachers may also feel that reasoning with context-rich data and uncertainty in statistical claims can make statistics difficult to learn and teach (e.g., [31,41]). Confidence to teach statistics is influenced by a teacher's beliefs, their experiences in learning and teaching statistics, and statistical understandings [31,42]. Eichler [40] posited that the focus of teachers' intended curriculum in statistics can be considered on a continuum from traditionalists (focused on procedures) to those wanting students to be prepared to use statistics in everyday life (focused on an investigative process tightly connected to contexts of real data). A goal in statistics teachers' professional learning is to move teachers along this continuum, which requires impacting teachers' beliefs about the nature of statistics and learning goals for students. In prior work, Lee and colleagues [27] showed that engagement in online professional learning for teaching statistics can shift teachers' perspectives about the nature of statistics and use of real-world investigations in their teaching and significantly increases their confidence to teach statistics.

To support students in developing productive statistical thinking, teachers need to carefully reconsider the use of procedurally oriented, teacher-centered learning environments. "Learning statistics is not about passively acquiring a set of facts and procedures but rather about actively constructing meaning and understandings of big ideas, ways of reasoning, and articulating arguments" [43] (p. 475). Ben-Zvi and colleagues [43] suggest that focusing on interrelated aspects of instructional design such as the tasks used and ways to orchestrate discussions about trends in data are needed to impact the way statistics is taught. Building from this, we argue that effective instructional design for supporting students' learning of statistics and data science should focus on seven interrelated dimensions and how each operates in relation to others: (1) developing students' thinking and practices of doing statistics in authentic ways; (2) focusing on central statistical ideas such as variability and uncertainty; (3) using well-designed tasks; (4) using real multivariate datasets; (5) supporting discourse and argumentation about claims with data; (6) integrating technological tools to support data processing and visualization; and (7) making sense of students' thinking in written, verbal, and technological work with data.

3. Design of the Online Platform to Impact Teachers' Learning

The design, development, and implementation of the InSTEP online personalized professional learning platform aims to support teachers' growth in knowledge and confidence are needed to create effective statistics and data learning environments. We hypothesized that personalized learning experiences focused on statistics content and pedagogy can effectively provide sustained engagement that results in motivating teachers to engage in learning opportunities aligned with their interests and goals, increasing teachers' confidence in teaching statistics, meeting teachers' professional growth goals, advancing their ability to create meaningful statistical learning environments for their students, and perceiving the personalized supports and learning materials as effective in supporting their learning goals.

The InSTEP platform is unique in several ways. Building from self-regulation learning theory, the design of incremental professional learning opportunities should help a teacher identify their goals and desired outcomes, and support the tracking of progress to achieve desired goals. A well-designed self-guided learning experience can also help learners develop self-regulatory abilities [17,44]. Features in the InSTEP platform are based on research-based design principles of effective online learning and include being self-guided and ongoing, contextualized and job-embedded, and learning from multiple voices that include experts, students' voices, and other teachers. The InSTEP platform also contains features to assist teachers in setting and monitoring goals, finding learning opportunities related to their interests, providing feedback, and tracking their progress. First, the platform provides opportunities for teachers to build skills in data investigations and innovative teaching approaches based on practices of data professionals and research on students' learning with data. Second, we personalize learning to meet teachers' professional needs through customized recommendations, allowing teachers to select learning activities based on these recommendations or other goals and interests [45].

3.1. Structure of Learning Experiences

A major goal of InSTEP is to support teachers' growth in knowledge and confidence to create effective statistical and data learning environments where all students are learning about important statistical and data ideas and engaging in key practices and processes to make sense of data. Central to our approach is building teachers' expertise in understanding interrelated dimensions of statistics and data learning environments that support students' reasoning about statistics and data [43]. Teachers have opportunities to engage with materials through two primary opportunities: (1) engaging in a data investigation module structured to help teachers experience the six phases of a data investigation process [46,47] through investigating a real-world phenomenon or issue with a larger multivariate dataset using an online data tool, and (2) learning with multimedia (text, video, images) materials organized in modules that include active engagement and opportunities to reflect.

The Learning Hub provides a visual interface of the organization of learning experiences that can also be used to navigate to specific experiences (Figure 1). The first type of learning experiences, data investigations, are organized by the Data Investigation Process (see top of Figure 1). This process helps guide teachers to investigate a problem or phenomenon using real data and a technology tool and provides opportunities for teachers to engage with data. Teachers are guided in exploration using the different data investigation phases: framing the problem, considering and gathering data, processing data, exploring and visualizing data, considering models, and finally communicating and proposing action as a result of making sense with data.

Modules, the second type of learning experience, are organized by seven dimensions (Figure 1) to support teachers in using well-designed tasks to support statistical thinking by engaging students in key data and statistical practices and processes to develop central statistical ideas about statistics and data. This approach involves integrating many opportunities for teachers to use real data to engage in investigations using technology tools that afford statistical and data practices. Our approach helps teachers learn to establish practices that promote productive argumentation and discourse, which include making and supporting data-based arguments, and the use of assessments of students' thinking about statistics and data to inform instructional decisions (not visible in Figure 1). Learning activities within modules are organized by essential resources, foundational materials to understand key ideas that are needed for module completion, and extended resources, which are materials that go beyond and may include classroom-ready resources.

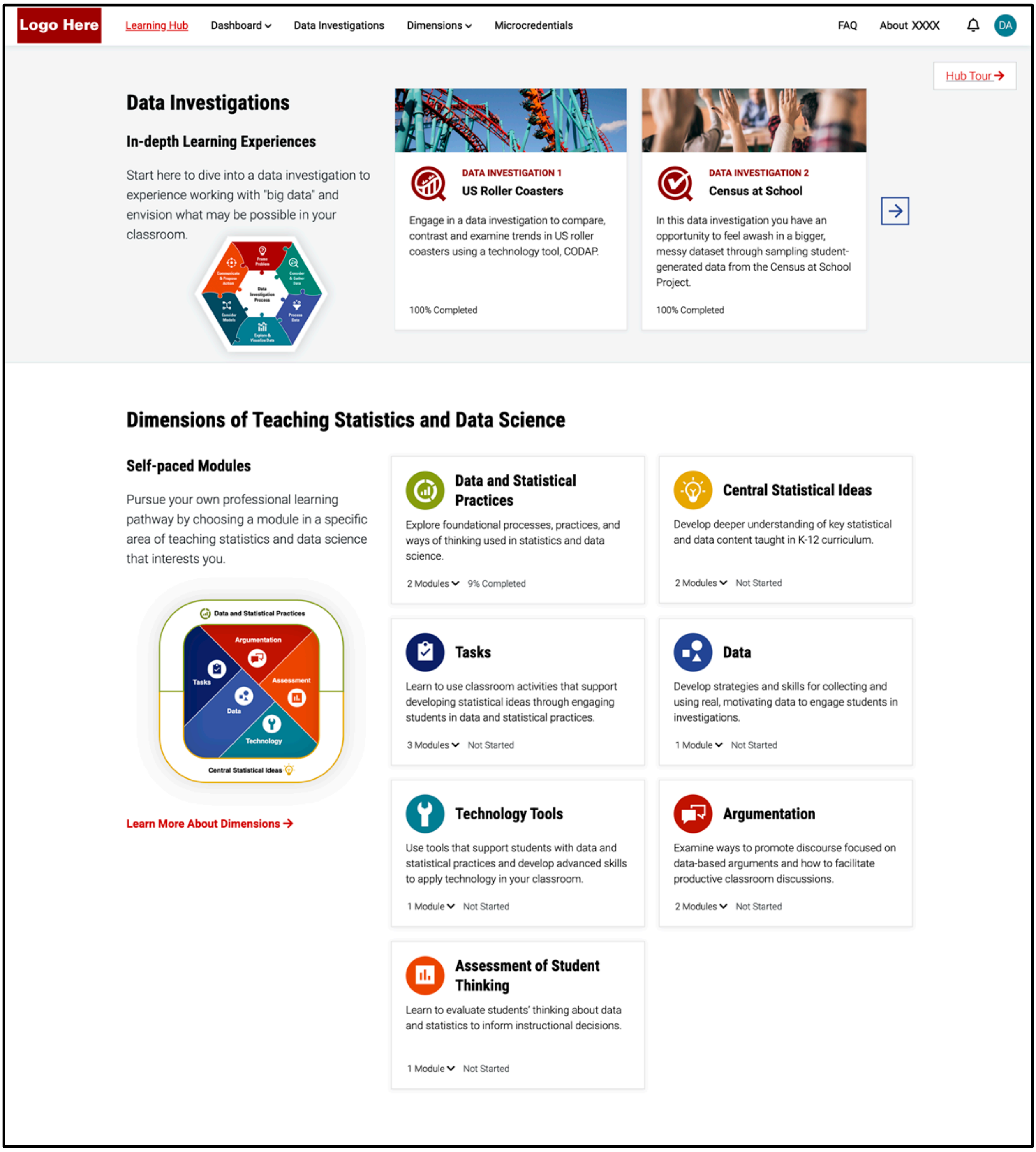

Figure 1. Learning Hub that organizes learning experiences by Data Investigation Modules and Self-paced Modules.

Table 1 includes the breakdown of all learning activities [30.2 h] available during the Fall 2022 field test study, the focus of this paper. Each page in a data investigation or module has time estimates assigned to help users guide their learning when they log in with limited time available for learning that day (see sidebar in Figure 2).

Table 1. Summary of learning experiences and time estimates for completion available during the Fall 2022 field test.

Learning Experiences and Hours Needed for Completion	Brief Title and Description
Data Investigations Module 1 Essential Resources: 9 pages, 1.9 h Extended Resources Hours: 1 page, 3.8 h (these extended resources are mostly part of other modules below)	Roller Coasters [RoCo]. A data investigation to compare, contrast, and examine trends in U.S. roller coasters using a large multivariate dataset of 635 cases.
Data and Statistical Practices Module 1 Essential Resources: 6 pages, 1.8 h Extended Resources: 8 pages, 3.1 h	What is Statistics and Data Science [S&DS]? Learn about the big ideas, habits of mind, and dispositions of statistics and data science.
Data and Statistical Practices Module 2 Essential Resources: 5 pages, 1 h Extended Resources: 8 pages, 2.2 h	Investigation Process [InvP]. Introduction to a 6-phase data investigation process that incorporates processes and practices of data scientists.
Central Statistics Ideas Module 1 Essential Resources: 5 pages, 1.6 h Extended Resources: 11 pages, 3.75 h	Big Ideas in Statistics [BIiS]. Introduction to the key ideas in statistics and how they are foundational for learning statistics.
Central Statistics Ideas Module 2 Essential Resources: 5 pages, 1.4 h Extended Resources: 10 pages, 4.7 h	Comparing Distributions [CDist]. Consider important concepts related to comparing distributions and their important role within statistics.
Tasks Module 1 Essential Resources: 6 pages, 1.9 h Extended Resources: 3 pages, 0.5 h	Worthwhile Tasks [WwT]. Explore what it means to identify and select worthwhile statistical and data tasks.
Data Module 1 Essential Resources: 6 pages, 2.1 h Extended Resources: 8 pages, 2.4 h	Data for Classrooms [DforC]. Learn strategies and how to get started in collecting and using real, motivating data to engage students in data investigations.
Discourse and Argumentation Module 1 Essential Resources: 6 pages, 2.9 h Extended Resources: 6 pages, 1.5 h	Discourse [Disc]. Introduction to components of effective classroom discourse and different ways to promote and support discourse while teaching statistics or data.

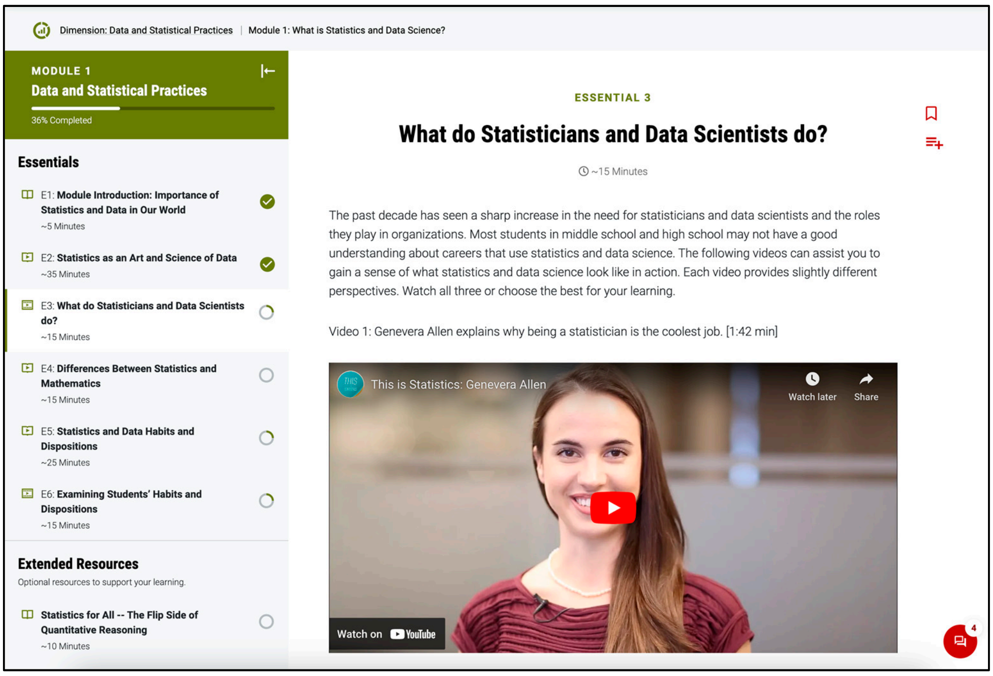

Figure 2. Example module with time estimates and tracking progress shown.

3.2. Supporting Personalized Learning

The platform is designed such that users can choose to engage in any learning experience that interests them in whatever order they choose. Thus, flexibility in when to engage and what to engage with is a primary way for the learning experiences to be personalized to meet a teacher's needs. We have four other design features that can assist teachers in making informed decisions for their learning and to keep track of what they have already completed.

The first design towards personalization is to provide recommendations to a participant. The use of recommendations in educational platforms is not a new endeavor (e.g., [48,49]). The purpose of recommendation systems in learning contexts is to assist users in making decisions and to help them feel comfortable to begin to navigate a free choice system. The participant is provided three recommendations at a time on the dashboard in a place to draw their attention and a statement describing how the recommendations were generated. This is a good design practice used for displaying recommendations in other educational systems (e.g., [49]). As one recommendation is completed, another recommendation replaces it based on a logic model that uses data collected from surveys our participants completed. Participants were given up to 6 total recommendations, and these are visible on the dashboard and profile page. More details on the recommendation logic model is in the Methods section.

The second design for personalization is based on recommendations from Kizilcec and colleagues [17] on strategies to assist learners in self-regulation behavior such as strategic planning and time management. We designed an internal tracking system and user dashboard that keep track of progress made on investigations, modules, and microcredentials (not examined in this study). Within a learning module, each page is given a time estimate, and when a user completes the activities on a page, they indicate completion, and the system keeps track of their completed work (Figure 2). The dashboard (Figure 3) provides a central place where a user can see all their progress and provides an easy way to resume their learning in a module or data investigation that they started but have not yet completed. With regard to tracking, users get credit for completing a module if they finish (and mark as complete) all essential resources within a module (i.e., extended resources contribute to hours earned but not module completion). Also, the dashboard displays their top three personalized recommendations and provides easy access to their progress towards meeting the necessary hours for each 10 h certificate, saved resources, playlists, and discussions (see right side of Figure 3).

The third feature for supporting teachers' personal learning experiences is the ability to save a resource and to collect specific resources into a "playlist" that they can name. These lists are then accessible from the users' dashboard (see right side of Figure 3) so that a user can quickly return to a specific resource from within a module without having to click through a module to remember where to find it. The fourth design to support personalization is a profile page where users see a report of survey results that includes details about the personal learning goals they chose in a survey, scores on a confidence survey and content assessment (described in Methods), and their top three recommendations for a suggested learning pathway (Figure 4). These displayed survey results can provide an opportunity for self-reflection and goal setting.

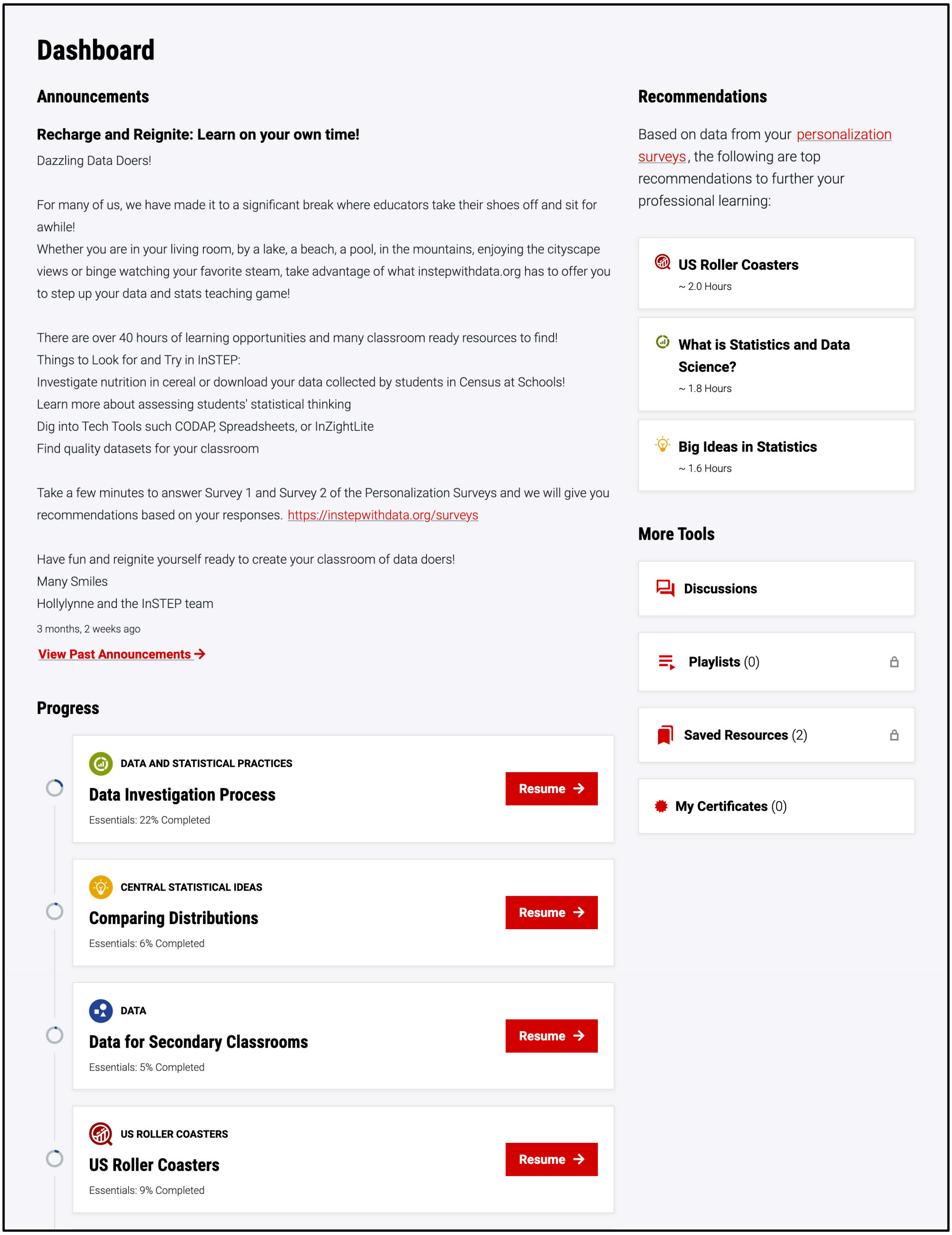

Figure 3. A user's dashboard showing recommendations, announcements, progress in completing the learning material, and access to saved resources and playlists.

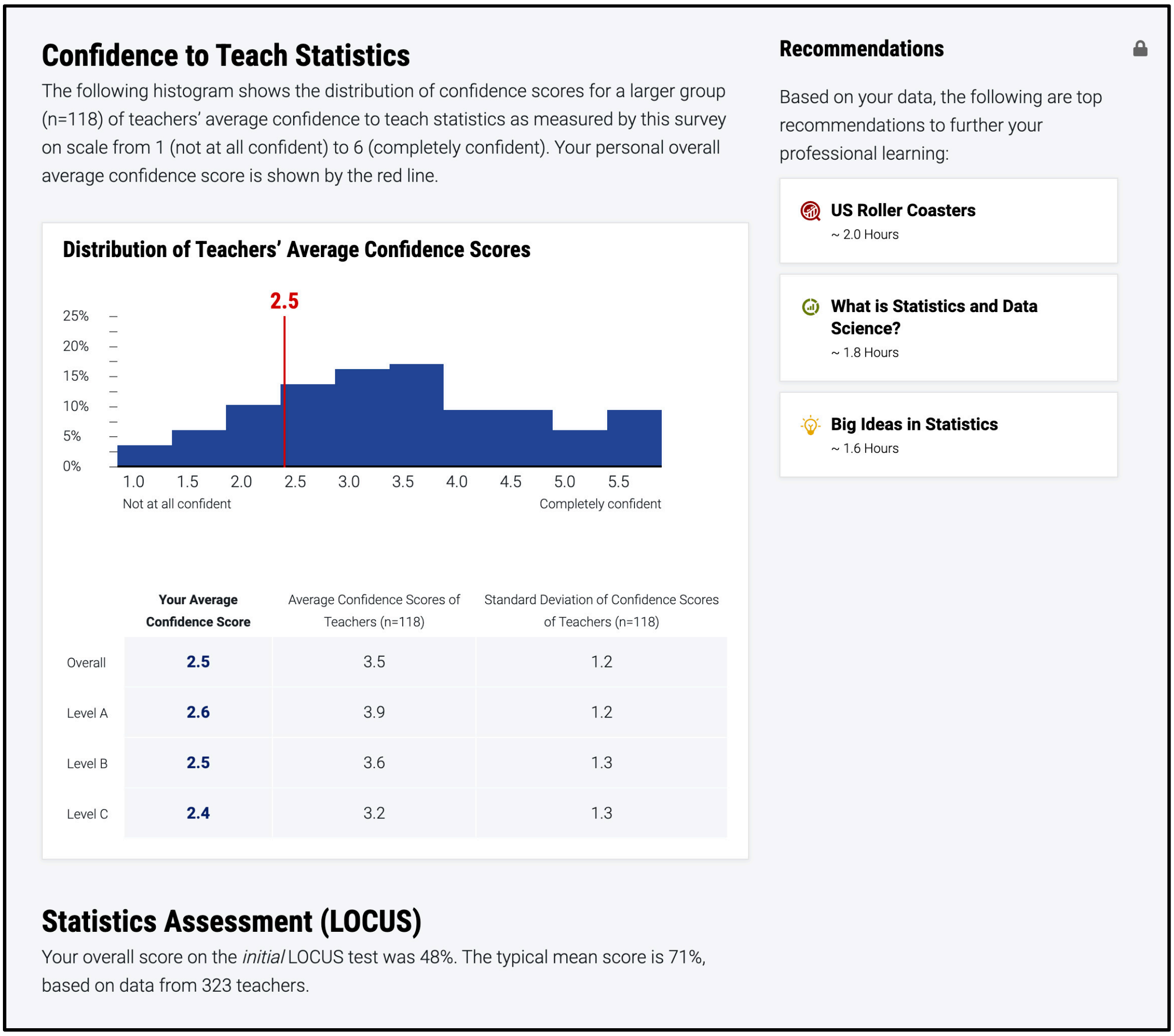

Figure 4. User's profile page with survey results and recommendations.

4. Methods

This research used a case study design [50]. Case studies are particularly a valuable methodology to explore how a group of people experience a contemporary event while using multiple sources of evidence. In this case, we explored ways in which teachers utilized different features and supports to personalize their learning in the InSTEP platform, and the platform's impact on the teachers' confidence to teach and classroom practices. Our case study, grounded in Mezirow's [14] theory of transformational learning in adult education and self-regulation theory [16], relied on a combination of qualitative and quantitative data to allow for "analytic generalizations" [50] that would support better understanding of how teachers engaged and were supported within the InSTEP platform.

4.1. Defining the Case

In Fall 2022, we recruited broadly (e.g., social media, listservs, personal contacts in school districts, and state supervisors), with a goal of recruiting 75–100 participants. Ultimately, 82 teachers chose to participate in a field test of the InSTEP platform. In this paper, we are focusing on a subset of these teachers to serve as a case study. Prior research on participation in online learning courses such as MOOCs has identified clusters of participants based on their engagement patterns and has always identified a subset of participants who have high engagement and are motivated to learn the content, complete courses, and earn certificates of completion (e.g., [29,30,51]). Thus, we wanted to examine more closely a subset of high-completion users to better understand the ways in which they engaged with learning experiences and how they used features in the platform designed to support their learning. Full participation in the larger field test included earning a certificate for completing 20 h of learning material. To be included in the case study for this paper, a participant had to meet the following criteria so that we would have consistent data across measures. Participants were paid incrementally for their participation for each of the following completed: (1) four pre-surveys with responses that led to personalized recommendations, (2) at least 20 h of professional learning (tracked activity with data logs), and (3) the post-experience survey. Thirty-seven participants met this criteria.

Our case consisted primarily of female identifying participants (78%) and included 27 mathematics/statistics teachers (16 high school, 9 middle school), 2 district-level math coaches, 7 science teachers (5 high school, 2 middle school), 2 middle school math and science teachers, and 1 middle school social studies teacher. These educators were highly experienced with a mean of 17.6 years (range of 5–31 years) in teaching/coaching and were employed in four states: California (n = 7), Iowa (n = 2), Maryland (n = 8), or North Carolina (n = 19).

4.2. Data Sources

To answer the three research questions, multiple surveys and assessments, as well as data logs, were collected and analyzed. Data included data logs and teachers' responses to the following: Goals and Background Survey, Self-Efficacy for Teaching Statistics (SETS), Levels of Conceptual Understanding of Statistics assessment (LOCUS), post-experience survey, and interviews. All surveys and assessments were conducted within the InSTEP platform. Below, we describe the data sources and indicate the research question each source is used to answer.

4.2.1. Instruments

At the beginning of the study, teachers responded to the Goals and Background Survey to collect data related to teachers' prior experiences and their professional goals. This survey also included demographic questions used to describe the participants. More details about how their professional goals were used are included in Section 4.2.3 describing the recommendation model, one of the personalization features we investigate in RQ3.

Prior to teachers' engagement with the InSTEP platform and, again, at the conclusion of the study, teachers responded to the SETS survey [52], a 44-item survey measuring teachers' confidence to teach students the skills necessary to complete specific statistical topics/tasks (e.g., use boxplots to compare the characteristics of two groups such as boxplots of test scores for males and females). Teachers rated their confidence using a 6-point Likert scale (ranging from 1—not at all confident to 6—completely confident). They also took the LOCUS assessment, a 23-item multiple choice statistics content assessment [53], which includes statistics content that is typically taught in grades 6–12 in the U.S. and is very similar to topics on the SETS instrument. Both instruments are used to answer RQ1.

At the end of study, teachers completed the post-experience survey so we could assess their overall professional growth from their learning experiences (RQ1) and their experiences engaging with personalization features of the InSTEP platform (RQ3). This survey consisted of 13 Likert scale questions using a 6-point or 7-point scale (very ineffective to very effective or strongly disagree to strongly agree), with multiple items for each question, and 4 open-ended questions. Frequencies and percentages for each rating were calculated for items focusing on the effectiveness of platform features. To analyze open-ended responses, we utilized open coding and constant comparative methods to identify emergent themes [54,55].

After 14 November 2022, if a participant earned a 20 h certificate, they were sent the post surveys to complete. After 28 November 2022, all participants were sent a reminder to complete their desired learning experiences and the post surveys, as we were closing the study on 4 December 2022. We had several participants in the larger study (n = 82) ask for extensions and, thus, we allowed a few to continue work and performed our last data download on 16 January 2023.

At the conclusion of the study, 7 of the 37 case study teachers participated in an interview focusing on teachers' experiences using the InSTEP platform. In the interviews, teachers were asked about how they used different features of the platform and to describe the typical ways in which they engaged over the study period. They were also asked about how what they had learned had impacted their practices. Since a structured interview protocol was administered, teachers' responses were summarized for each interview question, providing additional qualitative data describing teachers' experiences with various personalization features of the platform. Data from the interviews were used to better understand and situate other data sources for answering each research question. Teachers' responses to interviews and open-ended questions on the post-experience survey were used to provide examples and make sense of trends we saw from the quantitative analysis of datalogs, surveys, and instruments.

4.2.2. Data Logs

Data logs of teachers' engagement in the InSTEP platform captured how users were navigating through the platform and engaging with the different learning experiences. These data logs were essential in answering RQ2. Data logs captured individual views on all learning experience pages within the platform with the date and time. Additionally, data logs captured the date and times users marked a page as completed as well as the users' recommendations. The model for generating and displaying recommendations for a user is described next.

4.2.3. Recommendation Model

Recommendations are a critical aspect of the personalization features we designed into the platform and are used to investigate RQ3. Our approach to designing the recommendation system aligns with others who used ontology-based recommendation systems, specifically in platforms designed to support learning (e.g., [56,57]). "Most knowledge based e-learning recommender systems use ontologies to represent knowledge about the learner and learning resources. In such a case, ontology is used to establish the relationship between learners and their preferences about the learning resources" [57] (pp. 30–31). Our recommendation system is based on user inputs, including both psychological aspects (ranked goals and confidence to teach statistics) with cognitive aspects of a user's knowledge of statistics content typically taught in secondary schools. As designers of the learning experiences and experts in research on teachers' professional learning in statistics and data science, we created a mapping system to align certain goals, levels of confidence, and statistics knowledge to specific learning experiences in the platform.

While users can choose to engage with any of the learning experiences in any order they wish, we designed the online platform to support users' decision-making with recommendations based on the Goals and Background survey, LOCUS assessment, and SETS survey. Users receive up to six recommendations based on their responses to these surveys. Three recommendations for learning experiences were provided at a time and appeared on both the dashboard (Figure 3) and profile page (Figure 4) as stacked recommendations. To help avoid the "cold start" problem of users not knowing a place to start from or feeling overwhelmed in a system with many options to choose from [48,57], every user received the Roller Coaster and What is S&DS? learning experiences, even if they did not complete any surveys. The first two recommendations were given to allow users to experience one of each of the primary means of learning—a data investigation and a learning module since many users had limited experiences investigating real, large data as learners themselves and had limited experiences with key practices related to S&DS. The recommendation for What is S&DS? was based on material found in other studies to be highly influential in impacting teachers' beliefs and practices in teaching statistics through data [27]. In this way, the recommendation model uses a fixed system for all users to nudge them towards these important foundational learning experiences.

To determine the third initial recommendation, a question was asked within the Goals and Background survey to have users rank order at least five of nine learning goals according to what they would like to prioritize in their learning. The goal and the corresponding learning experience that most closely align from Table 1 are as follows:

It is important for my professional learning that I. . .

- Strengthen my understanding of key statistics and data concepts and skills. (BIiS)
- Strengthen my understanding of how to engage students in the practices related to statistics and data science. (IniP)
- Engage in real world data investigations with large data using technology. (RoCo)
- Deepen my ability to help students use data to make evidence-based claims. (IniP)
- Improve my ability to lead productive discussions about important ideas related to data and statistics. (Disc)
- Improve my ability to design, modify, and implement tasks to promote deeper understanding of ideas related to data and statistics. (WwT)
- Improve my ability to make sense of students' thinking through assessing their work, including written, verbal and technological. (Assessment 1, not available at time of study)
- Improve my ability to collect and use real-world data to support student's learning in statistics and data science. (DforC)
- Improve my ability to use technology tools to collect, process, visualize, and analyze data. (Technology Tools 1, not available at time of study)

Recommendation four and five were determined by users' scores on SETS and their statistics understanding as measured through the LOCUS assessment, respectively. The sixth recommendation was based on users' highest-ranked goal from their prioritized list that had not already been completed or given as a prior recommendation. The recommendation model did not include the Comparing Distributions module.

Recommendations are not explicitly numbered, but order is implied by placing them in a stacked appearance. As learning experience recommendations are completed, any remaining recommendations are added to the bottom of the recommendation stack. When a user completes enough experiences where there are less than three recommendations remaining, no new suggestions appear, and the ordered list continues to deplete with the same logic.

5. Analysis and Results

The primary aim of the InSTEP platform is to enhance teachers' expertise in teaching and learning statistics and data science by providing features that can support personalized, sustained engagement. First, we describe how we answered RQ1 regarding users' professional growth to teach statistics and data science through participation in the platform. After establishing the perceived effect of teachers' participation in learning with this platform, we investigate RQ2 by a close examination of participants' engagement within the platform through page views and module completion paths. Finally, we tackle RQ3 by analyzing participants' experiences with the features designed to support personalization. The analytic techniques used for each data source are described along with the results.

5.1. Growth in Expertise in Teaching and Learning of S&DS

This section aims to answer RQ1 regarding how participation in professional learning in the InSTEP online asynchronous platform contributes to professional growth in the teaching and learning of S&DS. Three data sources were used to examine the effects of the platform on teachers' perceived growth in the seven dimensions of the teaching and learning of S&DS (post-experience survey), their confidence to teach statistics (SETS), statistical content knowledge (LOCUS), and evidence of any incremental changes to classroom practices from the post-experience survey and interviews.

5.1.1. Perceived Growth in Dimensions of Teaching and Learning Statistics and Data Science

This platform frames expertise in teaching and learning using the Seven Dimensions framework. To help evaluate users' perceived growth within these seven dimensions, the post-experience survey asked about teachers' growth related to these dimensions. Users ($n = 37$) reported that overall, the InSTEP professional learning was effective (51%) or very effective (35%) in supporting their growth within the Seven Dimensions. There were three participants who indicated the professional learning experiences were very ineffective ($n = 2$) or ineffective ($n = 1$), though one of those participants rated everything else on the survey as positive and left a positive comment that, "I truly think the product is great!"; thus, it is not clear whether their low effective rating is valid. The two other participants had varied ratings across survey items and did not leave comments, so it seems those two participants likely had an overall ineffective learning experience.

Users also indicated their agreement for how well the professional learning experience helped them make progress in the nine personal learning goals that were listed on the initial Goals and Background survey (see Table 2), which align with the Seven Dimensions framework. For each item, there was a vast majority of users who agreed or strongly agreed that they were able to make progress towards developing their own knowledge and skills with statistics as well as their ability to enact effective strategies that align with the design of the modules and data investigations. There were three areas in which users reported the most agreement (agreed or strongly agreed) related to their progress: (1) strengthening their understanding of how to engage students in the practices related to statistics and data science (89.2%), (2) how to help students use data to make evidence-based claims (83.8%), and (3) their ability to lead productive discussions about important ideas related to data and statistics (81.1%).

Table 2. Distribution of agreement that participation in InSTEP professional learning helped them make progress towards specific learning goals.

***n* = 37**	**Percent of Teachers**					
	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Somewhat Agree**	**Agree**	**Strongly Agree**
Strengthening my understanding of key statistics and data concepts and skills. (BIiS)	0%	5.4%	0%	18.9%	48.6%	27.0%
Engage in real world data investigations myself with large data using technology. (RoCo)	0%	2.7%	8.1%	10.8%	43.2%	35.1%
Strengthening my understanding of how to engage students in practices related to statistics and data science. (IniP)	0%	0%	2.7%	8.1%	51.4%	37.8%
Deepening my ability to help students use data to make evidence-based claims. (IniP)	0%	2.7%	2.7%	10.8%	51.4%	32.4%
Improving my ability to lead productive discussions about important ideas related to data and statistics. (Disc)	0%	2.7%	2.7%	13.5%	56.8%	24.3%
Improving my ability to design, modify, and implement tasks to promote deeper understanding of ideas related to data and statistics. (WwT)	0%	2.7%	2.7%	27.0%	45.9%	21.6%
Improving my ability to make sense of students' thinking through assessing their work, including written, verbal and technological. (Assessment 1, not available at the time of the study)	0%	0%	2.7	32.4%	51.4%	13.5%

Table 2. *Cont.*

n = 37	Percent of Teachers					
	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Somewhat Agree**	**Agree**	**Strongly Agree**
Improving my ability to collect and use real-world data to support students' learning in statistics and data science. (DforC)	2.7%	0%	2.7%	24.3%	51.4%	18.9%
Improve my ability to use technology tools to collect, process, visualize, and analyze data. (Technology Tools 1, not available at the time of the study)	0%	5.4%	2.7%	18.9%	54.1%	18.9%

Two areas that users reported making less progress on were their ability to design, modify, and implement tasks (67.6%) and to make sense of students' thinking through assessing their work, including written, verbal, and technological (64.9%). At the time of the study, the platform did not include a module dedicated to assessment, so this makes sense (a module was added in 2023). However, a few videos in other modules included an opportunity to make sense of students' work using technology as well as examples of student work (e.g., examining posters of students' data investigations).

5.1.2. Examining Confidence to Teach Statistics

Of the 37 users, 36 of them completed both the pre- and post-SETS survey to assess their confidence to teach statistics. Recall that this survey measures confidence on a 6-point scale. We hypothesized that the post-confidence levels would be greater than the pre-confidence levels. The results of a paired-t test indicated that there was a significant large difference between their confidence before the professional learning experience (mean = 3.3, Stdev = 1.1) and their confidence measured after they received a 20 h certificate (mean = 4.5, Stdev = 1), t(35) = 8.8, $p < 0.0001$. The 1.2 mean increase in confidence score, small p-value, and Cohen's d effect size of 1.47 indicate that the magnitude of the difference between the average of the differences and the expected average of the differences is large.

5.1.3. Examining Statistics Content Knowledge

There were 32 of 37 users who completed both the pre- and-post statistics content assessment (LOCUS). Scores are the percentage correct out of 23 items. The results of the paired-t test indicated that there was a non-significant, very small difference between Pre-LOCUS (Mean = 72.4, Stdev = 18) and Post-LOCUS (Mean = 73.6, Stdev = 17.8), t(31) = 0.5, $p = 0.643$. While some teachers had large gains in their content score (e.g., +34%, +21%, +17%), others had decreases (e.g., −21%, −43%, −8%) or almost no change. Thus, as a collective, the professional learning experience did not appear to improve statistical content understanding. The LOCUS assessment was the last instrument users completed at the end of the study. Though they could complete these instruments in their own time over the span of a few weeks, we do wonder if assessment fatigue may have contributed to the ways in which users approached the post-LOCUS assessment. Additionally, with the focus of the LOCUS being on statistics content, only two modules would support growth on this assessment.

5.1.4. Self-Reported Classroom Changes

As in many professional learning projects with teachers, we did not have an opportunity to follow participants into their classroom to observe their classroom practices. Thus, we relied on a small amount of self-reported qualitative data. In the post-experience survey (n = 37) and interviews (n = 7), users were asked to comment on how their teaching practices had been impacted by learning experiences. Not all participants responded in ways that connected what they were learning to their classroom.

In the survey, 10 participants commented explicitly about how learning about and engaging in data investigation learning experiences (e.g., Roller Coaster, Investigative Process) were impactful because they “helped me model similar activities in my class” and “kept me the most engaged and allowed me to easily see how to bring it into the classroom”. A few specifically mentioned a plan to use the roller coaster data with students. As an example, one participant commented, “The rollercoaster activity ties in with a project our math and science classes do at the end of the school year. The data on rollercoasters was a great resource”. One teacher told us about a more general direct classroom impact related to implementing data investigations:

> “I have given my students two big data assignments as a direct result of [InSTEP]. One, I helped guide a little bit with questions and the second one I didn’t. The students said it was interesting and fun”.

Other teachers felt they learned a lot about pedagogical practices related to teaching statistics and data science that “gave me a new perspective about how to approach teaching statistics in middle grades science classes” and that they learned “the importance of using real and messy data to encourage true discussion”.

Some users expressed a desire for more classroom-ready lesson plans about specific topics or grade levels that they could implement in their classroom. One teacher reflected on their experience and noted how they really needed to gain more statistical knowledge to be able to impact their classroom practices.

> “Overall, I enjoyed the experience. I think for me personally since I am so weak when it comes to statistics, I need to build more background knowledge before diving more into the things on here. A lot of the things talked about are ideas that I wouldn’t know how to bring into my current classroom but am sure I could eventually get there”.

Another teacher specifically discussed the timing and coverage of statistics in their curriculum as a potential barrier for classroom change, though they indicated an intent for making a small change.

> “I thought the supports and resources were helpful and wonderful. My struggle is that my math curriculum does not include a lot of statistics and those topics are taught towards the end of the year. Although it is only touch on, I plan to give students more opportunities to collect and analyze their own data”.

5.2. Engagement in Professional Learning

Overall, our findings for RQ1 show evidence that the learning experiences had a positive impact on users’ growth in teaching statistics and data science. We next pursue RQ2 to examine in more detail the ways in which teachers engaged in learning experiences. This is examined through data logs that track views per day of learning experiences in the platform and tracking completion of modules.

5.2.1. Viewing Learning Experiences Across Study Period

Figure 5 shows the total number of page views in modules and the data investigation per day by all 37 case users. The view count does not include page views of when users were looking at the Learning Hub, their dashboard, playlists, profile, or taking surveys. To put these numbers in perspective, a typical module had 5–6 essential pages with 8–10 extended pages (not required for module completion) and the data investigation had 9 pages. Thus, on days in which there were 50 or less views, there could have been only a very small number of users engaging in learning experiences, while days with over 100 views likely consisted of page views of a large number of users. Throughout the study period, there were only 12 days when none of the 37 users were viewing a learning experience. Thus, as a group, they had sustained engagement, with August and November being particularly high.

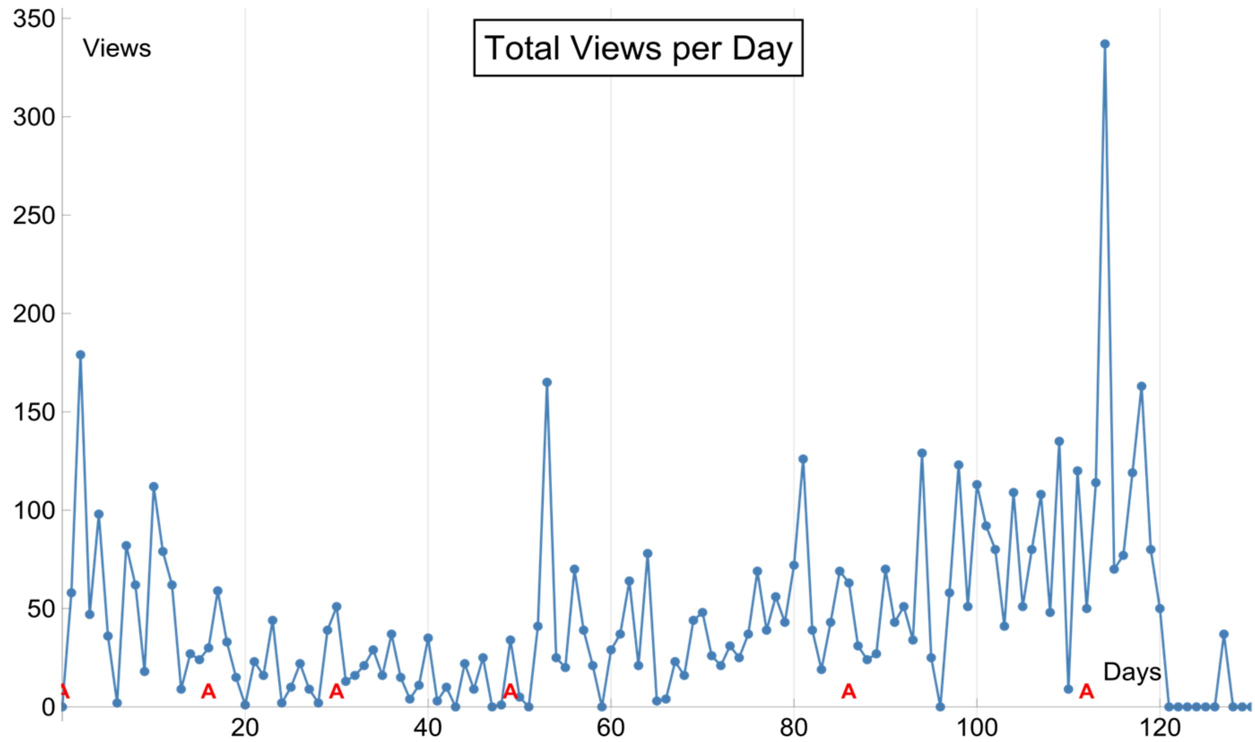

Figure 5. Time series of total views by 37 users of learning experiences (modules and data investigation) during the study period. "A" indicates when an announcement was sent to all study users.

The three major peaks (8/10, 9/28, and 11/28) in the time series all correspond with dates (indicated by an A) that users received emails about the project and reminders of expectations. The largest peak occurred shortly after an email on 11/28 announcing the official end of the field test (4 December 2022). There are also two main valleys in the time series. The first period of low engagement in September is most likely explained by users being busy with the new school year. The flatline at the end of the graph shows that while users still had access to the InSTEP platform, there were only two days of engagement by users (note: others in the larger field study group were active in trying to complete study requirements).

5.2.2. Patterns in Completion of Learning Experiences

The platform tracks views on pages with date and time as well as when a user indicates completion by pressing the Complete button at the bottom of a page. The two learning experiences with the most views (essential and extended resource pages) were What is S&DS? and Big Ideas in Statistics. Three modules had very similar view counts on the low end: Comparing Distributions, Worthwhile Tasks, and Discourse. Most users (59%) completed the Roller Coasters investigation first, with an additional 14% completing it second (see Table 3). There were two high school science teachers that did not complete Roller Coasters. What is S&DS? was the first or second experience completed for 73% of users, with all 37 users eventually completing this module. There were two additional modules that all users completed: Investigation Process and Big Ideas in Statistics. Only 26 users completed the Discourse module and 30 completed Comparing Distribution, even though a few more users viewed at least one page in those modules but chose not to complete them.

Table 3. Views and completions for each learning experience.

	RoCo	S&DS	InvP	WwT	BIiS	DforC	Disc	CDist
Total Views	704	1063	620	450	952	598	440	472
Users Viewed	36	37	37	37	37	34	31	32
Users Completed	35	37	37	35	37	32	26	30
Completion Order								
1st	22	8	5	0	1	0	0	0
2nd	5	19	7	2	3	2	0	0
3rd	1	6	17	4	7	0	1	1
4th	2	2	2	5	15	5	1	5
5th	1	2	3	10	4	4	6	7
6th	4	0	1	7	5	10	2	8
7th	0	0	1	5	2	7	6	8
8th	0	0	1	2	0	4	10	1

To further investigate patterns related to when users completed learning activities, we used the data logs of when a user clicked "complete" for each of the essential pages in the eight learning activities available to them. A module is considered complete once a user completes all essential pages in a module and does not consider their completion of any of the extended resource pages. For each user, we created a visualization of their learning experience completion over the period of the study. By examining all 37 visualizations, we looked for patterns in when and how quickly they completed modules. This process resulted in groups of users with similar completion behaviors. Through this process, multiple members of the research team proposed different groups of users that had similar patterns, and these were discussed and negotiated until the final six groups were made. The six groups are visualized in Figure 6a–f. The graphs show which learning experience they completed (vertical axis) on which day of the study (from day 0 to day 120). The red A markings indicate the days on which participants received announcements about the study. The six completion pattern groups are as follows:

A. Sustained Long Term: A user was engaged for at least 60 days with completions spread out over time. (n = 5)
B. Sustained with Sprints: A user was engaged for at least 60 days with completions spread out over time with at least two time periods where they completed two or more experiences within a day or two of each other. (n = 6)
C. Early Completion: A user started early in the study period and finished all their intended learning experiences within 60 days, some more quickly. (n = 6)
D. Late Start: A user did not complete any learning experiences until 40 days into the study period. (n = 8)
E. Deadline Motivated: A user started early in the period but completed several learning experiences within 3 days of the deadline for closing the study. (n = 5)
F. Super Sprint: A user completed most learning experiences in a 1–2 day time span. (n = 7)

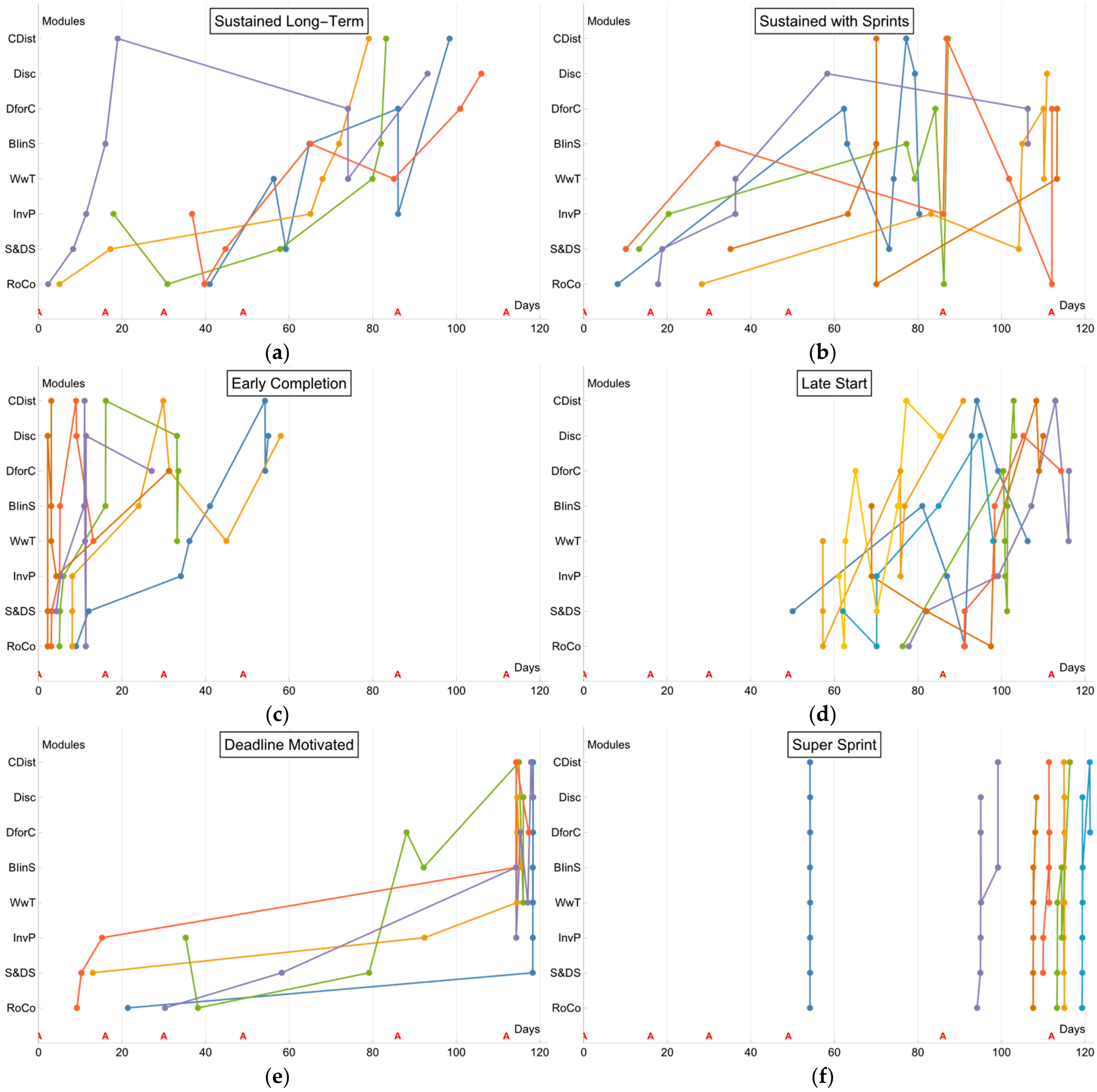

Figure 6. Six different completion patterns by users earning a 20 h certificate of completion: (**a**) Sustained Long Term, (**b**) Sustained with Sprints, (**c**) Early Completion, (**d**) Late Start, (**e**) Deadline Motivated, and (**f**) Super Sprint.

Though as a whole group it appears they had sustained engagement (Figure 5), there are distinct differences in the ways users individually completed the learning experiences. For the most part, the majority of users had sustained engagement within different time periods of the study, with only the Super Sprint group showing a very short completion time period. The completion pathways indicated that within the two dimensions that contained two modules, many users completed both modules in a linear order: specifically, 19 participants completed the two modules in Data and Statistics Practices in order and 21 did so within Central Statistical Ideas. The existence of different patterns of completion suggests that personalization and flexibility in when and how users could engage was supportive of self-guided learning towards completion and earning a certificate.

5.3. Participants' Use and Perception of Support for Personalized Features

To answer RQ3, we focus on a few of the features designed to support the ways a user could personalize the experience for themselves: recommendations, progress tracking, saving and grouping resources into playlists, and the profile page. We first examine what learning experiences users were recommended and how those compare with their completion pathways. We then examine users' perceived effectiveness of several other personalization features using the post-user survey responses and interviews.

5.3.1. Recommended Versus Completed Learning Experiences

At the time of the study, the recommendation logic model (described in Section 4.2.3) only provided a maximum of six recommendations matching six of the eight learning experiences that were available (Table 1). Recall that all users were recommended the Roller Coaster data investigation and the What is S & DS? Module, and the logic model did not include Comparing Distributions as a possible recommendation. Most users had either 5 (n = 15) or 6 (n = 21) recommended learning experiences, with one user receiving 4 recommendations. Table 4 shows the total times a module was recommended as well as the number of users that received a recommendation for a module in each of the positions. There were two learning experiences recommended to all users, and two modules (Worthwhile Tasks and Big Ideas in Statistics) recommended somewhere in their list to 35 (of 37) participants. Even though the Investigation Process module was recommended most in the third position, it appeared almost as often as the second replacement recommendation in the list for 9 users. Discourse was only recommended to 12 users, and its position in their lists was most often 3rd or 6th.

Table 4. Number of users given a recommendation for a learning experience.

	RoCo	S&DS	InvP	WwT	BIiS	DforC	Disc	CDist
Initial 3 recommendations	37	37	10	7	7	8	5	0
Replacement recommendation 1	0	0	2	28	6	0	1	0
Replacement recommendation 2	0	0	9	0	22	3	2	0
Replacement recommendation 3	0	0	7	0	0	10	4	0
Total	37	37	28	35	35	21	12	0

It is interesting to compare whether a user viewed at least one page or completed a learning experience (Table 3) and if that learning experience was recommended to them at all (Table 4). For four of the eight learning experiences, these three numbers were almost identical (Roller Coasters, What is S & DS?, Worthwhile Tasks, Big Ideas in Statistics). However, for the four other modules, even if a user was not recommended a module, many viewed or completed it. This indicates that users were choosing to engage with modules outside their recommendation list, which is indicative of the flexibility within the platform and users' choice making for what to learn more about. It is important to remember that the users in this case study were selected because they earned a 20 h certificate. Thus, completing modules is a highly popular way to earn these hours. Recall that users can earn time towards certificates by engaging with extended resources as well, which do not count towards module completion.

To examine how supportive recommendations, as a personalization feature, were for teachers' learning (part of RQ3), we analyzed each users' completion path and compared it to what was visible in their personal list of recommendations (three or less visible). For this analysis, we considered the first module that everyone completed as the first round of completions, the second completed module as the second round, and so forth. For each round of completion, we tallied the number of users who made a module completion and tallied those that diverged from their visible recommended pathway (top 3 or less, Table 5). For example, every user completed some first module, and for those 37 choices, 3 of them diverged from a users' visible recommendation list. As another example, only 31 users completed a sixth module while having non-empty recommendations lists, with all but 9 users following their recommendation.

Table 5. Actual and expected divergent choices from recommendations and probabilities of divergence.

	Round of Completion							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Number of completions by users	37	37	37	37	37	31	15	5
Number of actual divergent choices by users	3	8	8	8	14	9	2	0
Expected number of divergent choices under uniformly random assumption	23.1	21.1	18.5	15.4	12.8	11	7	0
Probability of actual divergent choices occurring	7×10^{-12}	1×10^{-5}	4×10^{-4}	0.008	0.7	0.3	0.02	1

To examine how often users diverged from their recommendation list, we applied probability principles to compute an expected number of divergent choices for each completion round. Then, we computed the probability of achieving the actual number of divergent choices participants made, all assuming that users made a uniformly random choice for which module to complete. Table 5 shows the actual and expected number of divergent choices as well as the probabilities for the actual number of divergent choices occurring in each round. The details of all expected values and probability computations are in Appendix A.

For the first four completed modules, the computed probabilities shown in Table 5 indicate it is highly unlikely that participants chose a module to complete in a random way considering the probability of each occurring is less than 0.01. These results are encouraging as they suggest a strong correlation between the visible recommendation list and the choices that participants made about which learning experience to complete and in what order, especially in the first 3–4 modules completed. It is possible that there were other contributing factors that informed their choices, such as the order of the modules within dimensions as shown on the Learning Hub page (see Figure 1 with Roller Coaster at the top of the page), users seemingly sprinting through the modules by clicking them all as completed (Figure 6f), and the fact that one module (Comparing Distributions) was not recommended to any user but was available to all. Starting at round five, the number of divergent choices recorded, 14 and 9, respectively, are not all that dissimilar to the expected divergent choices of 12.8 and 11 (Table 5). This could suggest that the correlation between the visible recommendation list and user choice of learning activity disappears after four recommendations. Some possible explanations could be that their experiences within the platform impacted their goals after the recommendations were generated, or that with only eight learning experiences, users' choice patterns changed.

5.3.2. Perceptions on Effectiveness of Design of Platform and Learning Experiences

The post-experience survey and interviews gave an opportunity for users to reflect on and share how different features in the platform supported their learning. Table 6 shows the distribution of perceived effectiveness for these features for these 37 users.

Table 6. Perception of effectiveness of personalization features to support professional learning.

***n* = 37**	**Percent of Teachers**						
How effective were the following features in supporting your professional learning?	Never Used	Very Ineffective	Ineffective	Somewhat Ineffective	Somewhat Effective	Effective	Very Effective
Recommendations	8.1%	2.7%	0.0%	0.0%	10.8%	29.7%	48.7%
Progress Tracking on Dashboard	5.4%	0.0%	2.7%	2.7%	0.00%	21.6%	67.6%
Progress Tracking within a Module	5.4%	0.0%	0.0%	2.7%	0.0%	13.5%	78.4%
Saved Resources	13.5%	0.0%	0.0%	5.4%	10.8%	27.0%	43.2%
Private Playlists	56.8%	0.0%	0.0%	5.4%	8.1%	16.2%	13.5%
Profile Page	10.8%	0.0%	2.7%	5.4%	24.3%	29.7%	27.0%
Data from Surveys on Profile Page	16.2%	0.0%	2.7%	0.0%	13.5%	32.4%	35.1%

Users were quite positive that the recommendations effectively (29.7%) or very effectively (48.7%) supported their professional learning, with only 8.1% (n = 3) reporting not ever using the recommendations. In interviews and in open-ended questions on the survey, users expressed appreciation for having recommendations that were based on their survey results and indicated they typically used them to inform their choices. This corresponds with our analysis showing that, in general, the users did not deviate much from their visible recommendation list. For example, one user commented:

> This program was excellent. The personalized plan based on my survey and the route it took me at first was a little confusing, but I eventually got that 'aha' moment. That could also have been because there were gaps between my being able to get online and work on this. (Sustained with Sprints participant)

However, one interviewee, a Super Sprint user, reported not using the recommendations and exploring the modules in an order of interest to them, typically navigating through menus at the top of the platform rather than the layout on the Learning Hub (see Figure 1). Examining this user's pathway of completion, though, showed only one divergent choice from the visible top three recommendations in their list. Thus, even though they reported not using recommendations, their choices and pathways indicate that the recommended list generated from their survey results may have been appropriate for their interests.

Almost all users reported that the tracking capabilities on the dashboard and within modules were effective or very effective in supporting their learning (Table 6). In interviews, teachers told us they used the tracking features to pick up where they left off when they logged back into the platform. Specifically, many users noted that within modules, they progressed linearly through material and used the left side-bar tracking (see Figure 3) to confirm "Yes, you did all of these things". For example, one user in the Early Completion group reported "It took me awhile to understand that I got to pick and choose [their own activities]", but that "the progress things helped a lot". One user from the Super Sprint group told us "I enjoyed the fluidity of the sessions where you had time to complete the assignments at your own pace and often I felt I rushed through some lessons. I used the self-checklist". Another teacher explained in an interview how tracking features helped them re-engage where they last left off since they often completed learning experiences in 20–30 min sessions during lunch or planning time and spent more extended times during the weekends (Sustained with Sprints user).

Most users took advantage of the feature to save resources, which were then easily accessible from their dashboard, and most thought this feature was an effective or very effective way to support their learning. However, many users (56.8%) did not use the private playlist feature where they could group saved resources into specific lists that had a personal meaning to them (e.g., "stuff for my classroom"). Those that did use playlists indicated it was an effective support for them, with one user commenting "The saved resource area for my playlist was VERY useful for things I wanted to return to". Others discussed in the interview that they would return to their saved resources or playlists to quickly find resources, and some mentioned they would print a PDF of the resource. One suggestion for improvement came from a user who thought it would be useful to be able to search the saved resources and playlists because sometimes they forgot where a resource was saved.

A little more than half of the users indicated the profile page, in general, was effective or very effective, and they were slightly more positive about the effectiveness of the data from surveys that were displayed on the profile page (see Figure 4) in supporting their learning and professional growth. Participants did not bring up the profile page or data from surveys as a source of reflection for supporting their learning in the open-ended questions on the post-experience survey. In the interviews, a few teachers noted that results from pre-surveys (SETS and LOCUS) "gave me an idea of what I was low on". A middle school math and science teacher explicitly discussed that they used results of the pre-surveys (SETS and LOCUS) to reflect on areas for growth and they tried to find learning experiences in the platform to help them improve but that there was not much they could find to help them with more advanced statistics content they wanted to grow in. Thus, we only have limited evidence for how a few users used the profile page and data from surveys to help them make choices and navigate the platform.

6. Discussion

We sought to answer three research questions using a case study of 37 secondary teachers (78% taught mathematics/statistics) who volunteered for a field test of the InSTEP professional learning platform. Related to RQ1, we saw evidence of incremental growth for our participants related to learning to teach statistics and data science. Recall that the learning experiences on the platform are structured and organized according to a framework of seven interrelated dimensions for teaching and learning statistics and data science [43]. Our participants perceived the InSTEP learning experiences as overall supportive of their growth in meeting the learning goals aligned with this framework, including a goal of engaging in data investigations themselves as learners. This aligns with prior research from Lee, Mojica, and colleagues about similar growth after learning experiences about teaching statistics in a MOOC format [26–28]. One learning goal that was rated lower in the current study involved designing, selecting, and implementing worthwhile tasks. While 35 participants completed a module on Worthwhile Tasks, the question on the survey also included implementation of tasks; thus, many teachers may not have had opportunities during the study period to focus on task selection, modification, and implementation if they were not currently teaching a course or unit that included statistics and data ideas.

Participants were likely motivated to join the research study and engage in professional learning because their personal professional learning goals aligned in some way with what they perceived as the goals of the learning material in the platform, based on advertising material and the website. Results from Barker and colleagues' [18] analysis of teachers' motivation for taking an online MOOC about teaching statistics through data investigations indicate that most teachers' motivation to enroll aligned with the course goals or a general goal of improving their knowledge and confidence to teach statistical topics.

We saw strong evidence for a growth in confidence to teach statistics, but little to no change in statistics content understanding for this group. The gains in confidence were unsurprising, and they align with prior findings that relatively short online asynchronous courses focused on teaching statistics improve teachers' confidence [27]. This finding makes sense since our platform focuses more strongly on pedagogy than further developing teachers' content understandings. The only modules that were directly aimed at strengthening teachers' understanding of specific statistics concepts were the two modules in the Central Statistical Ideas dimension. All 37 participants completed the Big Ideas in Statistics module and only 30 completed the Comparing Distributions module. The LOCUS assessment includes several items with advanced statistical content related to understanding *p*-values, confidence intervals, and linear regression. None of these concepts were included explicitly in modules in InSTEP at the time of the study. In a study of preservice teachers, Lovett and Lee [32] found that many of their participants' estimation of their confidence to teach statistics as measured through SETS was often relatively high, even while scores on the LOCUS assessment were low to moderate. Thus, having growth in confidence in being able to teach a topic in statistics is not only about one's statistics content knowledge but likely involves one's broader understanding of pedagogical strategies for supporting students' learning of statistics and having access to, or knowing where to find, good materials to use in the classroom.

Our second research question (RQ2) focused on ways in which participants engaged with learning materials. Through analyses of page views and completion patterns, there was evidence that our case of users had overall sustained engagement in the InSTEP personalization platform. Over the study's period, about 120 days, the teachers were engaged in viewing learning materials. We used a qualitative approach to classify users into different groups using their time series graph of when entire modules were marked as complete. We identified six engagement patterns that help better understand how participants can engage with a personalized online professional learning platform. We consider most of these patterns as representing sustained engagement just over different time periods (see Figure 6). The Super Sprint users were not considered to have sustained engagement as they completed all their modules within a few days. As many researchers have suggested, sustained engagement is considered a key feature of effective professional learning, whether online or in person [58–61]. Within research on MOOCs for educators, methods such as latent profile analysis have shown that teachers' engagement patterns over time are typically classified as consistent high engagers; mid-level engagement, which drops off near the end of a course's time period; and sharp drop offs for those that start a course and quickly have low to no engagement (e.g., [30,51]). The variety of completion patterns from this case study suggests that users utilized the personalized nature of the platform to engage when they wanted and for the length of time that worked best for them. Having a flexible format in an online professional learning environment where teachers can choose their learning pathways and have extended time to complete materials has been linked to a higher sustained engagement and completion certificates for teachers [62].

The third research question (RQ3) examined how personalization features supported users' professional learning within the platform. The personalization features that were considered most supportive were recommendations and tracking capabilities on the dashboard and within modules. These features are specific to supporting users in their navigation and choice of learning activities and seem to allow teachers to dive deeper into materials like extended resources that match their personal interests and needs. Situated in self-regulation theory, these features seem to support the user's ability to self-monitor their progress and quickly re-engage after extended time away from the platform, ultimately supporting their professional learning experience [16,44]. Kizilcec [17] and colleagues similarly found that goal setting and strategic planning supported online learners in their study.

Features that supported users to personalize learning through organizing materials they already engaged with (saved resources and playlists) or displaying results to surveys on the profile page had more mixed results. In fact, many users reported not using a playlist, and some users never used the profile page and saved resources. We suspect it is possible that users already had systems in place for curating resources for their teaching (e.g., Google Drive to save pdfs, bookmarking resources within their own browsers) and may have continued to use these instead of the ones built into the platform.

Our analysis comparing completion of modules to a user's recommendations provides additional evidence that the recommendation logic model generated a set of recommended learning experiences that were supportive to users through the first four recommendations provided. This finding provides support that a user input, ontology-based recommendation system that includes psychological aspects and cognitive aspects of a user's knowledge can support teachers' initial learning in an online setting. However, this finding also suggests that there could be value in incorporating a recommendation system that generates recommendations based on user behavior, such as patterns and profiles of similar users (near neighbors) [48,49]; such a recommendation system could support teachers' sustained engagement over time, not only through four recommendations.

Our case study with a small number of users has shown that using an asynchronous approach to online professional learning for teachers can be effective in helping them meet professional growth goals that appear to lead to incremental changes in their confidence and intent to implement new strategies or resources within their classroom. Now that the InSTEP platform is available to the public, we are very interested in expanding our research on teachers' engagement patterns and use of the recommendations with users who self-initiate their personal learning by voluntarily creating an account and choosing their own pathway.

7. Limitations

Case studies serve as an effective research method for examining multifaceted topics and yielding in-depth, contextual insights. However, this approach comes with certain limitations. The results of case studies are closely tied to the specific context in which they occur, making it difficult to generalize the findings to broader populations or other situations. This study took place with a group of teachers from the United States on a platform written in English. The socio-cultural context of our participants could have implications for our findings. In addition, we recognize that teachers' background knowledge and experiences in statistics likely varied due to their primary teaching responsibilities (math, statistics, science, or social studies) and influenced the ways they approached their professional learning in the platform and how they envisioned using their new knowledge, skills, and resources in their teaching practices. With such a small sample, we did not investigate any differences in engagement or professional growth through disaggregating by background or subjects taught. Such a nuanced investigation may be useful in future studies with a larger number of participants.

Additionally, we had a few limitations that could cause a lack of analytic generalizability. Both limitations involve conditions that may not accurately represent a broader setting. We had a small sample of volunteer teachers who were paid to participate in the field test study. While we suspect their engagement patterns may be representative of the ways in which teachers would engage on their own during a busy school year, the fact that they were paid to complete learning experiences could have influenced their engagement patterns. Additionally, the field test version of the platform only had eight modules for users to complete. Considering users were asked to engage in 20 h of learning, and these materials only covered 30.2 h, users may have completed learning experiences that they would not have chosen to complete without that requirement. However, users still had a free choice of order for those experiences.

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Appendix A. Computations to Support Analysis Comparing Users' Recommendations to Their Completed Modules

To compare a user's recommendations to their completed modules, we are only counting completions made while there was at least one recommendation visible to a user. There were 18 users that completed an 8th module (completed a module in the 8th round), but only 5 of them did so with a non-empty recommendation list. Since there are only eight modules, these five users had no choice but to complete the recommended modules, thus there were 0 divergent choices (see last column in Table 5). For the first round of module completions, each participant had eight modules to choose from, with three of them being recommended. If each of the 37 participants makes a uniformly random choice of their first module to complete, the expected number of divergent choices is 37x* (5/8) = 23.125 modules. Using the associated binomial distribution (shown below), we can compute the probability of having 3 or less divergent choices in round 1.

$$\binom{37}{0}\left(\frac{5}{8}\right)^{0}\left(\frac{3}{8}\right)^{37}+\binom{37}{1}\left(\frac{5}{8}\right)^{1}\left(\frac{3}{8}\right)^{36}+\binom{37}{2}\left(\frac{5}{8}\right)^{2}\left(\frac{3}{8}\right)^{35}+\binom{37}{3}\left(\frac{5}{8}\right)^{3}\left(\frac{3}{8}\right)^{34}\approx 7\times 10^{-12}$$

For the second round of module completions, each participant had seven modules to choose from, with three of them being recommended. If each of the 37 participants makes a uniformly random choice of their second module to complete, the expected number of divergent choices is 21.1429 modules. Again, using the associated binomial distribution, the probability of having eight or less divergent choices is approximately 1×10^{-5}.

When choosing their third module to complete, there was one participant that only had two modules on their recommendation list, as their recommendation list had only four modules, two of which were the ones completed by this participant. However, the remaining 36 participants still had three modules in their list of recommendations, and all participants completed a third module from a remaining list of six available modules. Thus, it is very reasonable to consider the third round using the same binomial distribution approach. If each of the 37 participants makes a uniformly random choice of their third module to complete, the expected number of divergent choices is 18.5 modules. Using the associated binomial distribution, the probability of having eight or less divergent choices is approximately 4×10^{-4}.

As we look at the cases for four or more completed modules, the number of recommendations seen by some participants does begin to drop below 3, making a binomial distribution approach inaccurate. Instead, we used a Monte Carlo approach to build approximate distributions for the remaining rounds of module completions and to estimate the expected value and probabilities of the actual number of divergent choices occurring.

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