ABSTRACT

BARKER, HEATHER A. Motivation, Engagement, and Professional Growth of Participants in Online Professional Development Courses for Statistics Educators (under the direction of Dr. Hollylynne Lee).

The increased statistics standards in K-12 mathematics curriculum, the rise of enrollment in Advanced Placement Statistics in high schools, and increased enrollment in introductory statistics courses in college, have led to a rising need of quality professional development (PD) for teachers of statistics. Online professional development (OPD) is a timely and convenient way to provide high quality PD for those that teach statistics as well as create an online community of educators. Massive Open Online Courses for Educators (MOOC-Eds) have been created to provide these opportunities. The increase of enrollment in MOOCs in general has led to research around what motivates people to enroll in such free open courses as well as investigate the behaviors of participants as they engage in courses. Less research has been done to investigate the ongoing professional growth of participants after they have engaged in a course. This study investigates the motivation, engagement and professional growth of participants who enrolled in two successive MOOC-Eds, *Teaching Statistics through Data Investigations (TSDI)* and *Teaching Statistics through Inferential Reasoning (TSIR)*. TSDI was offered 7 times from 2015-2018, and TSIR was offered 3 times from 2017 - 2019. The 1,592 participants of the study were those who accessed at least the first unit of at least one course.

This study uses a sequential mixed methodology that had two phases. The first phase used quantitative methods to group participants by factors based on motivation and engagement using cluster analysis. Motivation factors came from answers to an enrollment survey question asking about why participants enrolled in a course. Another source for motivation used topic modeling to identify themes for motivation from the discussion forum posts in an introductory

forum. Three groups of participants were determined, those that enrolled for reasons that aligned to course objectives (*professional learners for teaching statistics* and *statistics investigators)* and those that enrolled to gather resources (*teaching resource collectors)*. Another cluster analysis was done to identify groups of participants by how they engaged in the course. Three clusters were found, *highly active course completers*, *consistent course completers*, and *least active course fizzlers.* There seemed to be no relationship between groups based on motivation and engagement, except when the data was disaggregated by those who enrolled in both TSDI and TSIR. People who took both courses that were *professional learners for teaching statistics* and *statistics investigators* seemed to have a higher proportion of people who were *highly active* or *consistent course completers.*

Phase 2 included a qualitative assessment of a follow up survey sent to the 1,592 participants. This survey was sent at least a year after any participants had enrolled in any of the courses. The survey included questions about how the course(s) affected their knowledge, beliefs, professional practice, and any salient outcomes such as student outcomes, ongoing changes to teaching, and influence on the community around them. Survey results were promising, showing that the courses had a positive impact on their professional growth.

The findings of this study suggest that offering OPD for statistics educators is a meaningful way to provide PD. Additionally, the impact of offering two successive courses is evident when looking at the higher engagement rate of those who took both courses. Results suggest that those offering OPD should consider this model of sustained duration when designing such courses. The findings also offer methodological insight for other researchers exploring participation in open online courses, such as topic modeling and cluster analysis.

Motivation, Engagement and Professional Growth of Participants in Online Professional Development Courses for Statistics Educators

by
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BIOGRAPHY

Heather Barker was born in Newport News, Virginia on November 30, 1983, alongside her twin sister and best friend, Jillian Mickens, to parents Tammy Carter and Keith Allmond. Tammy and her daughters returned to her hometown of Semora, North Carolina in 1986, where Heather would also eventually settle down with her own family. Heather was fortunate to have a close relationship with her father, and fortunate to gain a loving stepfather, Johnny Goggin. The love and support of her parents and sister helped her support her through her life's journey.

After completing high school in 2002, Heather attended Meredith College in Raleigh, North Carolina as a first-generation college student. There she received her bachelor's degree in Mathematics and Religion. From 2006 – 2008 she taught mathematics at Bartlett Yancey High School in Yanceyville, North Carolina, the same high school she and her parents (and her grandparents) attended. She loved teaching mathematics to students who grew up where she did. In 2008 she began a master's degree in Pure Mathematics at the University of North Carolina at Greensboro. Upon graduation, she accepted an appointment as a mathematics instructor at Piedmont Community College in Roxboro, North Carolina where she taught from 2010-2015. This was a very formative experience, helping her realize her knack at creating online curriculum as well as a passion for teaching statistics. From 2015 – 2017 Heather accepted a position at Elon University teaching statistics, where she was encouraged by the faculty to pursue a PhD.

In 2011, she married her childhood friend, David Barker. David and Heather had been close friends since kindergarten, only living two miles apart. And now they live together on his family's farm, two miles from her parents. They have two amazing children, Forrest (born 2014) and Annie (born 2019). Forrest and Annie are the light of her life and make every day better.

In Fall 2017, Heather began her PhD in Learning and Teaching in STEM Education in the STEM Education Department at NC State University. While working on her PhD, Heather also completed a doctoral minor in statistics. She will graduate in December 2021. She joined the mathematics and statistics department at Elon University again in Fall 2020 and intends to continue teaching their as long as they'll have her. Heather is fortunate to be able to teach both statistics as well as teacher preparation courses for the next generation of mathematics and statistics teachers.

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I would especially like to thank my family for supporting me through this PhD journey. My husband, David, and children, Forrest, and Annie, who would not let me give up. My sister, Jillian, and brother-in-law Ross have always been a never-ending source of support. My sweet sister-in-law, Hannah, continually checks on me and makes sure I'm okay. I cannot say thank you enough to my parents, Tammy and Johnny, and my in-laws Margaret (rest in peace), Cherie, Dennis, and Bobby who kept the children so many times with no complaint so I can work. Finally, to my neighbors who are also my sisters, Elizabeth, Mary, and Scarlett, thank you for your constant encouragement and humor.

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CHAPTER 1 INTRODUCTION

Background

An increased focus on the role of statistics in mathematics education has led many educational researchers to rethink not only how statistics is taught in the mathematics curriculum (Langrall et al., 2017), but also how to better prepare in-service teachers to teach statistics (Burrill & Biehler, 2011; Pratt, Davies, & Connor, 2011). A shift in how statistics is incorporated in the classroom has been influenced by several publications. The National Council of Teachers of Mathematics (NCTM) pushed for the inclusion of statistics in the K-12 curriculum in the publication of the *NCTM Standards* in 1989 and again in 2000 (NCTM, 2000). With the rising call for a statistics content domain within math classes, the Common Core State Standards for Mathematics in the United States included a domain focused on the teaching of probability and statistics, which starts in 6th grade and continues through high school mathematics (CCSSM, 2010).

The American Statistical Association (ASA) endorsed the Guidelines for Assessment and Instruction in Statistics Education (GAISE) report in 2007 (Franklin et al., 2007). The *GAISE College Report* was then released in 2016 to guide the way undergraduate statistics courses are taught due to the influence of the changes made to the grade 6-12 mathematics curriculum (Carver, et al., 2016). With the successful influence of the GAISE standards to influence statistics curriculum, the ASA released *GAISE II* in 2020, with updated recommendations for making sense of data today (Bargagliotti, et al., 2020). Updated changes to statistics curriculum because of these publications have led to a call for professional development specific to statistics for those whose pre-service teacher education were not influenced by the incorporation of statistics into the mathematics curriculum (Franklin, et al., 2015; Lovett & Lee, 2017).

Significance of the Study

The *Statistical Education of Teachers* (SET) report, commissioned by the ASA, stresses the need for professional development at the local or state level to aid mathematics teachers to teach statistics (Franklin, et al, 2015). Since many in-service teachers were in pre-service programs that did not require many statistics courses, the SET report states that "robust professional development opportunities need to be developed for advancing in-service teachers' understanding of statistics" (Franklin, et al, 2015, p.6). The SET report and statistics education researchers assert that professional development opportunities specific to statistics, especially the statistics investigative cycle, helps increase confidence in mathematics teachers to teach statistics (Souza, Lopes, & Pfannkuch, 2015).

Though the SET report realizes the need for professional development programs specific to statistics education, it also admits the limitations of providing these sorts of opportunities at local levels (Franklin et al., 2015). Fortunately, there are online opportunities for professional development specifically designed for statistics teachers (Lee & Stangl, 2015). Online professional development (OPD) can be a convenient way to create a community of learners, as well as provide PD that is on demand and timely. With the increase of offerings and enrollment of participants in large online professional development courses, such as Massive Open Online Courses (MOOCs), it is important for those who are creating and facilitating OPD for statistics teachers to understand the impact of these efforts on educators.

Purpose and Focus of this Study

Two successive massive open online courses for educators (MOOC-Eds) were offered for those interested in improving their statistics pedagogy, *Teaching Statistics through Data Investigations* (TSDI) and *Teaching Statistics through Inferential Reasoning* (TSIR). These courses were offered a total of l0 times from 2015 – 2019. This study examined the motivation, engagement and professional growth of educators who engaged in these courses. The first course, TSDI, was created to help instructors implement the statistical investigation cycle through data investigations. The second course, TSIR, was meant for instructors who have a strong foundation of the statistical investigation cycle to further their own understanding of using and teaching statistics through inferential reasoning. Each course was meant to enhance teachers' statistics teaching strategies in middle school through introductory level college courses.

This study builds on frameworks and theory for motivation and engagement in online learning as well as models for professional growth to describe why people took the courses, how they engaged in the course, and what effect the courses had on their current professional practice. The study began by identifying factors for motivation through topic modeling of discussion forums. Then groups of participants were identified based on motivations for taking a course and how they engaged in a course through cluster analysis. An exploration followed to identify if a relationship exists between motivation and engagement behaviors for these participants. Finally, an attempt to describe professional growth was done through a sample of participants who completed a follow-up survey. The study was guided by the following questions:

1. *How can participants across two online professional development courses for*

teachers of statistics be characterized based on their motivation for taking the course(s) and their engagement during the course(s)?

   a. *What motivates participants to enroll in online professional development courses for statistics educators?*

      i. *In what ways can topic modeling be an effective tool to identify motivation of participants who enroll in online professional development courses for statistics educators?*

   b. *How do participants of OPD for statistics educators engage in the courses?*

   c. *How is motivation for enrolling in OPD for statistics educators related to how participants engage in the course(s)?*

2. *How did participation in statistics education online professional development impact ongoing professional growth for participants?*

To answer my research questions, I used a sequential mixed methodology approach (Ivankova et al., 2006; Ivankova, 2014) that consisted of two phases, quantitative analysis followed by qualitative analysis. The first phase used cluster analysis to group participants based on factors related to *motivation* for taking the course and *engagement* trends while enrolled in the course. The second phase of the study used qualitative analysis of a follow-up survey sent to participants of the courses about ongoing changes in their practice as well as other salient outcomes because of their participation in the courses.

Organization of the Study

Chapter 2 will present a review of the literature on teaching statistics, professional development for teachers of statistics, engagement and motivation in online learning, and modeling teacher professional growth. Chapter 2 also includes a proposed framework for this study. The methodology and results of this study are organized into 3 journal ready articles. Chapter 3 will present an outline of methodology for the entire study, but details of the methodologies will be shared in the journal ready articles (chapters 4, 5, and 6). Chapter 4 presents a journal ready manuscript concerning ways that topic modeling was used to describe participant motivation in TSDI and TSIR. Chapter 5 presents a journal ready manuscript describing motivation and engagement of participants in TSDI and TSIR using cluster analysis. Chapter 6 presents an article for a magazine synthesizing the findings of motivation and engagement as well as sharing the preliminary findings from the survey on professional growth. Chapter 7 will present a summary and discussion of the findings, as well as implications for statistics educators, and suggestions for future research.

Important Definitions

- Massive Open Online Courses for Educators (MOOC-Eds) – these courses provide large scale and accessible professional development opportunities for educators. They are free, usually self-paced, and have opportunities for continuing education credits.
- Teaching Statistics through Data Investigations (TSDI) – this course was offered through the Friday Institute for Educational Innovation as a MOOC-Ed. The course was meant to help statistics educators to deepen the knowledge and skills necessary for teaching students using data investigations.

- Teaching Statistics through Inferential Reasoning (TSIR) – this course was offered through the Friday Institute for Educational Innovation as a MOOC-Ed. This course emphasizes inferential reasoning in teaching statistics through posing different types of investigative questions.
- Online Professional Development (OPD) – any professional development that has some or all its materials in an online format.
- Course participant – a person that has enrolled in one or both of the two courses that are part of this study, and accessed at least the first unit of at least one course
- Teacher of statistics – an educator who teaches statistics as part of their curriculum. This includes teachers where statistics appears as a part of the curriculum they are required to cover or teachers who teach an entire course devoted to just statistics. This includes K-12 teachers, college/university teachers, or pre-service teacher educators.

CHAPTER 2 LITERATURE REVIEW

The literature review provides an overview of the research that will inform the study as well as frameworks that will situate the study. I will begin with an overview of the importance of statistics education in the mathematics curriculum, followed by specific knowledge, skills and dispositions needed for teaching statistics. The next section will share professional development for teaching statistics, including opportunities for online professional development (OPD) specific to teachers of statistics. The next sections will move away from specific literature about teaching statistics, and instead focus on research that has investigated motivation and engagement of online learners. This section includes an overview of research methods specific to online learners, specifically topic modeling and cluster analysis. Next a framework for describing professional growth is shared. Then prior research that has been done on the two courses of this study, TSDI and TSIR, will be explored. The section on prior TSDI and TSIR research is framed around motivation, engagement, and professional growth of participants. Finally, a framework that was used for this study is presented.

Statistics Education Overview

Statistics has been steadily gaining ground in mathematics curricula. Forty-two states, the District of Columbia and four territories of the United States have adopted the Common Core State Standards and within the CCSS for Mathematics, Statistics and Probability are included in grades 6-12(CCSS, 2010). The College Board introduced the Advanced Placement exam for statistics in 1997 to meet the growing demand of introductory statistics course requirements in colleges and universities (Piccolino, 1996). In 2007, 98,033 students took the AP statistics exam. By 2017 that number has more than doubled to 215,840 (College Board, n.d.). Statistics has made an impact in the mathematics curriculum, which has led to challenges in preparing teachers to teach statistics.

In many colleges and universities, the study of statistics and mathematics has taken place in separate departments. “Statisticians are convinced that statistics, while a mathematical science, is not a subfield of mathematics” (Cobb & Moore, 1997, p. 814). Since mathematics and statistics are separate fields, the knowledge needed for teaching statistics is usually lacking for a mathematics teacher that has been prepared to teach through a traditional mathematics program that may require as little as one undergraduate level statistics class (Groth, 2007; Tintle et al., 2014). Since there is a difference between statistics and mathematics, the knowledge, skills and dispositions for teaching statistics will also differ from those specific for mathematics.

Knowledge, Skills, and Dispositions for Teaching Statistics

Though it has long been understood that being able to decipher meaning from data is an important skill, the explicit inclusion of statistics in curriculum has often been overlooked (Gal, 2002; Garfield & Ahlgren, 1988). The world that students encounter today is driven by data, and it is important that students can interpret the meaning of this data around them in an educated way (Gal, 2002; Usiskin & Hall, 2015). For students to be able to develop these skills they must have teachers that are effective in teaching and fostering knowledge, skills, and dispositions specific to statistics.

Just as mathematics teachers should have content knowledge of mathematics beyond that of their students, so should teachers of statistics (Franklin, et al., 2015). Elementary and middle grades teachers usually learn the content needed to teach statistics in an introductory college statistics course (Franklin, et al., 2015); however, there is no uniform introductory statistics course across academic institutions (Carver et al., 2016), even though many institutions allow AP credit for those passing the AP Statistics exam. The SET report recommends that high school mathematics teachers take three courses in statistics: an introductory course, a statistical methods course, and a statistical modeling course (Franklin et al., 2015). These courses should follow the GAISE framework and guidelines in their development and instruction.

Statistics education researchers have recommended content knowledge that is important for teachers of statistics. Burrill and Biehler (2011) include knowledge of data, variation, distribution, representation, association, and modeling relations between two variables, probability models, sampling, and inference as fundamental ideas for teachers to know and include in their instruction. Pfannkuch and Ben-Zvi (2011) list data, patterns in data, distribution, variability, and inference as the five key statistical concepts that form the foundation of improving teachers' statistical thinking. The content knowledge needed for each teacher will vary based on grade level of instruction and local standards.

Since many in-service and pre-service mathematics teachers take less statistics courses than are recommended by the SET report, this leads to teachers who are underprepared in teaching statistics concepts. Assessment instruments have been created to measure conceptual understanding of statistics (delMas et al., 2007; Jacobbe et al., 2014). Using these instruments, it has been shown that many pre-service high school mathematics teachers have about a middle school level of conceptual understanding of statistics (Lovett & Lee, 2017) or similar to the understanding of undergraduate students who are not in quantitative disciplines (Hannigan et al., 2013). Since the pre-service teachers in these studies will eventually be responsible for teaching statistics in mathematics curriculum, these results suggest that professional development is needed to foster in-service teachers' conceptual knowledge of statistics.

Having content and conceptual knowledge of statistics is important but having the pedagogical knowledge to be able to teach students may be more important. Though many pedagogical skills unique to teachers of statistics exist, I will focus on engaging students in the statistical investigation cycle and incorporating technology into statistics instruction.

Statistical Investigation Cycle

Wild and Pfannkuch's (1999) landmark paper described the investigative cycle in statistical inquiry as five phases of a cycle: problem (define the problem), plan, data (collect data), analysis, and conclusions. Building on this definition of an investigative cycle, the GAISE framework promotes four phases of a statistical investigation: formulating questions, collecting data, analyzing data, and interpreting results (Franklin et al., 2005). For most statistical investigations in classrooms the entry point is the analysis phase, the questions have already been posed and the data has already been collected. The challenge for teachers is to develop students' inquiry skills to help support them in the investigative cycle (Makar & Fielding-Wells, 2011).

Many teachers get stuck in the procedural features of investigations but being able to guide students through a statistical investigation is an important skill for teachers to possess (da Ponte & Noll, 2018). A particular issue for teachers in engaging students in statistical inquiry is managing the uncertainties that can arise. Designing professional development that engages teachers in statistical investigations can help prepare them to manage these uncertainties and gain confidence to engage students in the statistical investigation cycle (Makar, 2010; Makar & Fielding-Wells, 2011).

Technological Pedagogical Statistical Knowledge

A critical skill for teaching statistics is the ability to incorporate technology throughout classroom instruction. Biehler et al. (2013) use the metaphor that learning statistics is like traveling between two points where “travelling is never ending: reaching a conclusion can raise further questions; conflicting conclusions can raise doubts, caveats, or even rebuttals” but that the “role of a computer tool is to make travelling (whichever way) easier and faster” (p. 678). It is not just important that educators learn how to use new technologies, but it is also important that “in order for effective learning to take place, it is how the technology is integrated into the curriculum and learning process and how the teacher uses it that are vital” (Pratt, Davies, & Connor, 2011, p. 98). Research has shown that students who engage in using real data through the Internet and statistical software packages show not only better understanding of concepts, but they are also more enthusiastic during statistical investigations (Connor et al., 2006).

With the increasing use of innovative software for statistics classrooms, it is easy to support the idea that technology is “an integral part of teaching, learning and reasoning processes” (Pfannkuch & Ben-zvi, 2011, p. 324). Because of the importance of technology in statistics classes, a framework for teaching statistics with technology is needed. Mishra and Koehler (2006) introduced the *Technological Pedagogical Content Knowledge (TPCK)* framework as the intersection of 3 components of teacher knowledge: content knowledge, pedagogical knowledge, and technological knowledge. The Venn diagram they suggest also includes overlapping areas of just two domains such as *Pedagogical Content Knowledge (PCK)* as described by Shulman (1987). Lee and Hollebrands (2011) introduce a framework for teachers, *Technological Pedagogical Statistical Knowledge (TPSK).* TPSK expands on the TPCK framework by supporting the idea that teachers of statistics not only need to know how to teach with technology, but teachers of statistics should have additional knowledge of teaching with technology specifically for statistics.

Beliefs and Dispositions of Teachers of Statistics

The dispositions and beliefs that teachers have while teaching a statistics class can influence how students perceive the subject. An important belief that teachers of statistics must possess is that mathematics and statistics are different disciplines that require different instructional methods (Groth, 2007). Eichler (2011) found that the students' perceived importance of statistics is affected by how teachers enacted the curriculum. When teachers used context and relevant data in their teaching, students found value in statistics. But when teachers used an algorithmic way of teaching, more like mathematics, students did not see the point of learning statistics.

Having confidence in their ability to teach statistics is also an important disposition that teachers should possess. Pre-service and in-service mathematics teachers often lack the confidence to teach statistics if they are underprepared in their training. The Self-Efficacy for Teaching Statistics (SETS) Survey is a tool that measures mathematics teachers' knowledge and beliefs about teaching statistics (Harrell-Williams, et al., 2019). Using the SETS survey, Lovett and Lee (2017) concluded pre-service teachers in their study were not prepared or confident to teach statistics upon graduation.

Professional Development for Teachers of Statistics

Professional development opportunities for teachers of statistics have been implemented to foster the knowledge, skills and dispositions addressed above. The SET report outlines two recommendations for professional development: teachers should be able to develop a deep conceptual understanding of the statistics they will teach, and they should be actively engaged in the statistical investigation cycle (Franklin et al., 2015). In addition to these recommendations, keeping statistics educators up to date with current technology that is available for statistical investigations is essential in promoting statistical thinking in students (Biehler et al., 2013; Pratt et al., 2011). This section will feature some of the professional development efforts to meet these recommendations and challenges.

Professional Development to Foster Conceptual Understanding of Statistics

The GAISE framework emphasizes that students should have a conceptual understanding of statistics instead of just the ability to perform statistical procedures (Franklin et al., 2005). It is one thing for a student to be able to calculate the p-value of a hypothesis test and draw a conclusion, but to know what the p-value is saying about the context of the data is conceptual understanding. Professional development efforts focused on key statistical concepts, such as measures of center, variation, and distribution, helps teachers move past rote mathematical computations of statistics, to true deep conceptual understanding of statistics.

Professional development that allows teachers to explore statistical measures can greatly increase their understanding of why those measures are important. For instance, most in-service teachers can easily compute measures of center, such as mean, median and mode, but many lack the conceptual understanding of what measures of center represent in a distribution of data (Franklin, et al., 2015). During a yearlong PD for middle and high school mathematics teachers, Peters et al. (2014) designed “PD tasks with planned triggers for dilemmas” (p. 1). The tasks included hypothetical students’ work on correct and incorrect ways to represent and interpret "typical" in a dataset. After engaging in these tasks, teachers were able to shift their conceptual understanding away from only computations of measures of center, to a deeper understanding of measures of center as a "balancing point" in a set of data. During the same PD session, teachers also engaged in tasks that challenged their understanding of measures of variation such as standard deviation and mean absolute deviation (Peters & Stokes-Levine, 2019). After the PD session many teachers noted that they finally fully understood measures of variation, despite their own experience in taking statistics courses and even teaching the ideas in their own courses (Peters & Stokes-Levine, 2019).

Kuzle and Biehler (2015) designed a professional development where practicing teachers became "mentor teachers", who would then conduct a professional development for other teachers of statistics. Unfortunately, the researchers found that after 5 months of intensive professional development, most of the activities carried out by the mentor teachers stayed on a developing level and did not help with deep conceptual understanding. Though these researchers had evidence for increased conceptual understanding at the end of the PD, the lasting effect of this conceptual understanding after the PD has ended needs to be explored.

Professional Development for Engaging in the Statistical Investigation Cycle

Professional development focused on the statistical investigation cycle is important so that teachers can "proficiently engage students in statistical inquiry and support them through the investigative cycle" (Makar & Fielding-Wells, 2011, p. 352). Souza et al. (2015) followed two middle school teachers as they engaged in a professional development using a statistics investigation cycle and found that their approach to teaching statistics as a mathematics course changed because of being engaged in the investigation cycle. Lee et al. (2020) investigated participants of an online professional development for practicing teachers based on conducting statistical investigations with students. Many of the teachers who engaged in this professional development not only reported an increase in their confidence to teach statistics, but they also reported shifts in beliefs that statistics should be taught using investigations, not just as a mathematical tool devoid of context.

Makar and Field-Wells (2011) followed participants of two different professional developments designed to teach teachers to use statistical investigations and found that over two years teachers became more proficient in engaging their classrooms in the investigative process. They concluded that the following key characteristics are needed to develop teachers' skills of teaching using statistical inquiry: long-term support and resources, engaging in statistical investigations as learners, learning that is embedded in classrooms, deeper statistical content knowledge, engaging teachers in collaboration and providing opportunities for reflection.

Engaging in statistical investigations as learners can help in-service teachers increase their own content knowledge of statistics. McClain (2009) led a professional development course for middle school teachers to increase their understanding of univariate distributions of data. After engaging in statistics investigations as students, teachers were better able to describe distributions of data beyond simply looking for measures of average. Dolor and Noll (2015) used a guided reinvention approach during a ten-week professional development course to help pre-service and in-service develop a hypothesis test for categorical data. Dolor and Noll concluded that using a constructivist approach to statistical inquiry helped the participants to develop a deeper understanding of hypothesis testing.

Professional Development to Foster Technological Pedagogical Statistical Knowledge

Keeping statistics educators up to date with current statistical technology is essential in promoting statistical thinking in students (Biehler et al., 2013; Pratt et al., 2011). The SET report recommends that professional development programs for high school teachers should have teachers "use dynamic statistical software or other modern appropriate technology" (Franklin et al., 2015, p. 33). Ensuring that teachers incorporate technology into their statistics classrooms is not easy, but it is important to developing statistical thinking (Lee & Hollebrands, 2011). Much of the research on teachers' use of statistics technology has focused on pre-service teachers experience with technology, because of the easy access researchers have to PSTs at their own institutions (DePonte & Noll, 2018). More research on the use of statistical software among in-service teachers is needed.

Teachers are more likely to teach with technology they know and are comfortable with, even if it is not the most effective in fostering statistical thinking (Biehler, et al., 2013; Lee & Hollebrands, 2008). To foster the use of dynamic statistical software that teachers may not feel comfortable using, teachers must have experience with using it so that they can appreciate how powerful it can be in understanding statistics. Wassong and Biehler (2014) led a four-month long course for mathematics mentor teachers on incorporating statistical software into grades 5-10 mathematics curriculum. Initially the course developers wanted to use Excel and Fathom (Finzer, 2002), a dynamic statistical software tool, in data investigations. After the fourth meeting the mentor teachers requested to only focus on the use of *Fathom* after seeing how much more effective using Fathom can be to create data visualizations, instead of the static data visualizations created in Excel.

Madden (2014) led a professional development for secondary teachers where they first engaged with a statistical task physically, and then they used dynamic statistical software to complete the investigation. She concluded that engaging in technology these ways empowered teachers to try similar methods in their own classrooms. Lee et al. (2020) found that many teachers participating in an online PD centered on statistics investigations expressed that "engaging in statistics is enhanced by using dynamic technology tools" (p. 12).

Research has shown that teachers appreciate the benefits of using dynamic statistic software during PD, but it has also been found that after engaging in PD participants may not be ready to engage their own students in statistics investigations using the technology (Lee & Nickell, 2014). The transition from calculator use to computer use is difficult. These difficulties stem from the fact that many schools do not have funding for computers or software, beliefs that students will have trouble learning new technologies and teachers' reluctance to learn new technology (Lovett & Lee, 2017). Though confidence and excitement about using new technology may be high at the end of a PD, what happens to teachers once they are back in their own classrooms?

Online Professional Development for Statistics Teachers

The SET report states that statistics teacher educators should support statistics teachers at all levels by helping K-12 teachers have knowledge and skills of teaching statistics beyond what was required for their initial certification, encourage teachers to strive for continual improvement in their teaching, and join with teachers to learn at all different levels (Franklin, et al., 2015). But these goals can be especially difficult for statistics teachers who many feel isolated, i.e. one high school teacher that teaches all the statistics courses in his school which is the only high school in the district. Also, teachers have busy schedules beyond just teaching in their classrooms. Thus, having professional development opportunities that are online can help teachers develop knowledge and skills that may otherwise be unattainable in a face-to-face setting (Lee & Stangl, 2015).

Though there have been blended online PD opportunities, where part of the experience is face to face and part is online (Akoğlu, 2018; Akoğlu, et al., 2019; Wassong & Biehler, 2014), there have been far fewer *fully online* PD experiences for teachers of statistics. Building on the recommendations from GAISE, Garfield and Everson (2009) designed a fully online course for statistics educators modeled after a face-to-face course previously taught in the graduate program at their institution. Though the course was a requirement for graduate students in their statistics education program, it often attracted teachers of statistics from high school and local colleges. The move to an online format was an attempt to serve more in-service teachers who may be interested in increasing their statistical pedagogical knowledge. Evaluation of the course revealed that many in-service teachers not only felt they learned from the experience, they also intended to encourage others to take the course and join local networks of statistics educators for regular meetings.

EarlyStatistics was an online professional development course in statistics education created for European middle and high school teachers. The course aimed to improve teachers' pedagogical and content knowledge of statistics as well as creating a professional learning community across countries (Meletiou-Mavrotheris, 2011). Participant feedback provided positive evidence that the course met its intended objectives. Though the course developers felt that the course provided a positive experience for its participants, there was also evidence that misunderstanding of statistical ideas arose because of language barriers and differences in state and national curricula (Meletiou-Mavrotheris et al., 2009; Serradó-Bayés et al., 2014).

Other online PD has included MOOCs (Massive Open Online Courses) that focused on statistics pedagogy (Lee & Stangl, 2015). Stangl and her team developed the *Teaching Statistical Thinking* MOOC which was intended for in-service high school mathematics teachers. This MOOC consisted of three components: core, pedagogy, and software. The MOOC begins with an introduction of descriptive statistics, lessons on implementation of descriptive statistics in the classroom, followed by a focus on software that can be used for descriptive statistics (Lee & Stangl, 2015). Lee and her team created two MOOCs titled *Teaching Statistics through Data Investigations (TSDI)* and *Teaching Statistics through Inferential Reasoning (TSIR).* Each course is meant to enhance teachers understanding of statistics and teaching strategies in middle school classes through introductory level college courses. Prior research of the impact of these courses on participants will be thoroughly explored in section *Prior TSDI and TSIR Research.*

Engagement and Motivation in Online Learning

The rise of Massive Open Online Courses (MOOCs) has led many researchers to explore participant motivation for enrolling in a course, as well as patterns of engaging in course materials (Frankowsky, et al., 2015; Perna, et al., 2014; Thompson, et al., 2016; Wilkowski, et al., 2014). For curriculum developers and course instructors, "the goal for curriculum development has typically been to create a linear sequence of content in an optimal order of increasingly complex content. As computer-based (eLearning) instructional environments became more prevalent, there arose more interest in the flexibility and the usability of instructional content and its delivery mechanisms" (Wiebe & Sharek, 2016, p.55). This new sort of course design attracts a diverse group of learners with varying goals to MOOCs. Because of this diversity, models for motivation can and should be linked to patterns of engagement that emerge for participants in these courses (Thompson, et al., 2016). This section includes prior research on motivation and engagement in online learning, specifically MOOCs.

Motivation in Online Learning

Self-determination theory can help in understanding engagement and motivation by exploring the conditions that motivate humans to initially engage in challenging tasks (Wiebe & Sharek, 2016). According to self-determination theory, motivation can come from intrinsic or extrinsic influences and factors. Intrinsic motivation is when an individual may pursue a task for the sheer human pursuit of learning or creativity. On the other hand, extrinsic motivation comes from outside influences or awards that require the completion of a task (Eccles & Wigfield, 2002; Wiebe & Sharek, 2016). Defining one's motivation as intrinsic or extrinsic is not always obvious. An individual may enroll in a course such as TSDI with the singular goal of learning about the statistics investigation cycle. This could be an example of intrinsic motivation. Another individual may enroll in TSDI with the goal of getting a certificate of completion to meet required hours of PD in their school--this is an example of extrinsic motivation. If we revisit the first person and find out later that he only wants to learn about the statistics investigation cycle because this is part of a new standard that must be taught in his math classes, then the motivation can also be classified as extrinsic.

Another issue that can arise in determining an individual's motivation is that goals for engagement can change over time (Winne & Baker, 2013). One could assume that individuals enrolled in a MOOC all have the same goal of learning the materials in that MOOC. The autonomy of participation in a MOOC with the ability to engage as little or as much as desired during the course can mean "that users are allowed to formulate widely differing sets of goals for their engagement in the course" (Wiebe & Sharek, 2016, p. 67). A participant of a MOOC may indicate she is taking the course to receive a certificate of completion during an enrollment survey, but after engaging in one or two units may decide she has learned what she needed and not complete the entire course.

Researchers have agreed that earning a certificate of completion or *finishing* a MOOC is not the only measure of participants' success (Wilkowski, et al., 2016). This is especially true for MOOC participants that are already highly educated and may not need to earn a certificate of completion (Bonafini, 2017; Emanuel, 2013; Hollebrands & Lee, 2020). This is not meant to say that extrinsic motivation of earning credits should seem any less noble than intrinsic motivation to learn. Extrinsic and intrinsic motivation are meant to be classifications, not rankings.

Extrinsic motivation can also arise from being part of a social group (Moore & Wang, 2020; Wiebe & Sharek, 2016). For instance, in the TSDI course a participant must post in all 11 discussion forums to earn a certificate of completion. Posting in the forum is a type of engagement that may simply be extrinsically motivated by an individual's desire to complete the course. But perhaps an individual posts in forums because he is motivated by the need to discuss his thoughts on materials in the course with others. As previously stated, oftentimes educators may be isolated as the only teacher in a school teaching statistics content. Having a sounding board, such as a discussion forum in TSDI, may be the extrinsic motivation needed to engage in the course.

Identifying motivation for enrolling in a MOOC is often achieved by asking questions on enrollment surveys (Creager, et al., 2018; Hollebrands & Lee, 2020; Moore & Wang, 2020; Wilkowski, et al., 2014). Wilkowski et al. (2014) sought to identify groups of individuals based on their motivations for enrolling in a MOOC hosted by Google. Participants were asked about their motivation on the enrollment survey. The possible answers included learning about aspects of the course as well as earning certain certificates. The research team then conducted a follow up survey for participants to determine if they reached their intended goal. The only goals that were met at least 50% of the time were those that were satisfied after engaging in the first 1 or 2 units of the course. Similar results have been used by MOOC developers as the reason for placing the most important materials early in the course (Hollebrands & Lee, 2020).

Latent profile analysis (LPA), a form of latent class analysis, has been used to classify participants of a MOOC by their motivation for enrollment (Moore & Wang, 2020). Moore and Wang (2020) examined the responses of an enrollment survey for a MOOC offered by Harvard University to determine if any underlying profiles for students' motivations to learn could be identified. Using LPA, they found that students could be best grouped by one profile, intrinsic or extrinsic learners. Intrinsic learners tended to choose motivations for taking the course as lifelong learning, learning about course content, or curiosity about online learning. Extrinsic learners chose answers such as advancing my career or participating in an online community. Moore and Wang found that those who were grouped as intrinsically motivated tended to have higher rates of course completion. This is an interesting finding since earning a certificate of completion was one of the factors that was part of the extrinsic motivation group.

Engagement in Online Learning

The open nature of MOOCs has led many educational researchers to analyze participant engagement in the courses. Being able to measure and describe engagement can help inform course design for future course developers (Thompson, et al., 2016), be used to describe clusters of participants by engagement (Frankowsky, et al., 2015), or help with the creation of technology that can give real time feedback to participants on their progress towards meeting their goals (Wilkowski, et al., 2014). This section will explore different ways that engagement has been measured. Specific research on engagement in TSDI and TSIR will follow in a later section.

Linear models have been created to determine if engagement in a course can be used to predict course completion. Perna et al. (2014) analyzed data from 16 first time MOOC course offerings to determine if participants proceeded sequentially through a course and if there were certain milestones in the courses that could predict course completion (defined as accessing the last unit). It was found that participants did tend to progress sequentially through the course even if they registered for the course late. There was a steep drop-off of participants that accessed the first and second modules. This steep drop-off has been noted by other educational researchers studying patterns of engagement in MOOCs (Clow, 2013; Frankowsky, et al., 2015; Hollebrands & Lee, 2020; Thompson et al., 2016). After looking at several course milestones, such as accessing at least one lecture in the first module, Perna et al. (2014) found that no milestones were predictive of course completion. This was especially hard to measure since less than 12% of registrants in all 16 courses were considered course completers.

Wiebe, et al. (2015) argue that research in engagement in MOOCs needs to move past descriptive statistics such as those used in the Perna, et al. (2014) study, and move toward a more person-centered approach. A "person-centered approach does not assume that the effect of a given variable is linear, and it accounts for many complex interactions with other variables in a model" (Wiebe, et al., 2015, p. 253). Cluster analysis is an exploratory analysis method that can be used to classify participants into clusters, or groups, when a classification of groups is not known (Frankowsky, et al., 2015). Cluster analysis was used to group participants of a MOOC-

Ed into different clusters based on their engagement with resources over time (Frankowsky, et al., 2015; Wiebe, et al., 2015).

Latent class growth analysis (LCGA) has proven to be a “robust, accurate, and informative approach that allows prediction of cluster membership from individual characteristics” (Thompson, et al., 2016, p. 5). LCGA was used to create clusters of participants of a MOOC-Ed, based on their interaction with certain resources in the course during each week, demographic data, and self-reported motivations for joining the course (Thompson, et al., 2014; Thompson, et al., 2016). This analysis led to defining three groups, *high stable* (those that engaged in a high steady use of the course), *medium stable* (consistent utilization of resources over time, but clear exclusion of some resources), and *declining and volatile group* (similar to medium stable initially, with a steady decline after week 2) (Thompson, et al., 2016). This research helps support the hypothesis that MOOC participants consist of separate groups based on their motivations for taking the course and their engagement during the course.

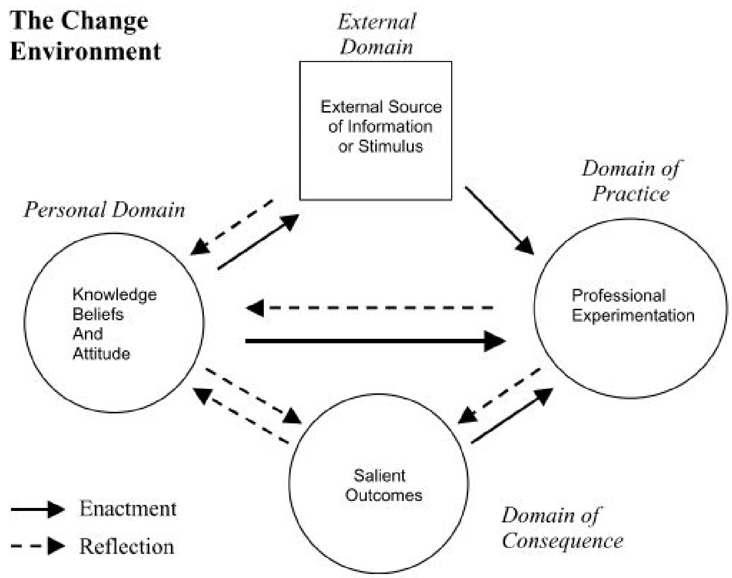
A Model for Teacher Professional Growth

Since professional development is required of most K-12 teachers, defining effective professional development is important. Desimone (2009) has been often cited for her literature review which was used to create a framework for defining important aspects of effective PD for educators. Building on Desimone’s work (2009), Darling-Hammond et al. (2017) identified seven characteristics of effective PD (content focused, calls for active learning, uses job embedded contexts, contains models and modeling, provides coaching and expert support, opportunities for feedback and reflection, and is of sustained duration) . Often PD is considered effective when most of these seven characteristics are featured in the PD design. Yurkofsky, Blum-smith and Brennan (2019) argue that the Desimone (2009) model of what constitutes effective PD assumes that the improvements in teacher knowledge, instructional practice, and student learning are the most valuable outcomes. These outcomes are hierarchical in nature in that teacher knowledge leads to improved practice which then leads to better student outcomes. Assessing the effectiveness of PD in this linear progression can be limiting, especially since it can often be difficult to capture the change that may occur in a teacher's practice over time (Kennedy, 2016).

Instead of this hierarchical linear progression of impacts from PD, Yurkofsky et al. (2019) suggest that the Interconnected Model of Professional Growth (IMPG) presented first by Clarke and Hollingsworth in 2002 may be a better model for online PD which often provides multiple pathways for learning. The interconnected model of professional growth offers multiple ways that teachers may gain new content knowledge, experiment with their teaching practice, and influence their students (Clarke & Hollingsworth, 2002). Since the ways that a teacher may engage in a MOOC-Ed varies, it makes sense to use the Clarke and Hollingsworth (2002) model to describe the varied professional growth I expect to see from participants.

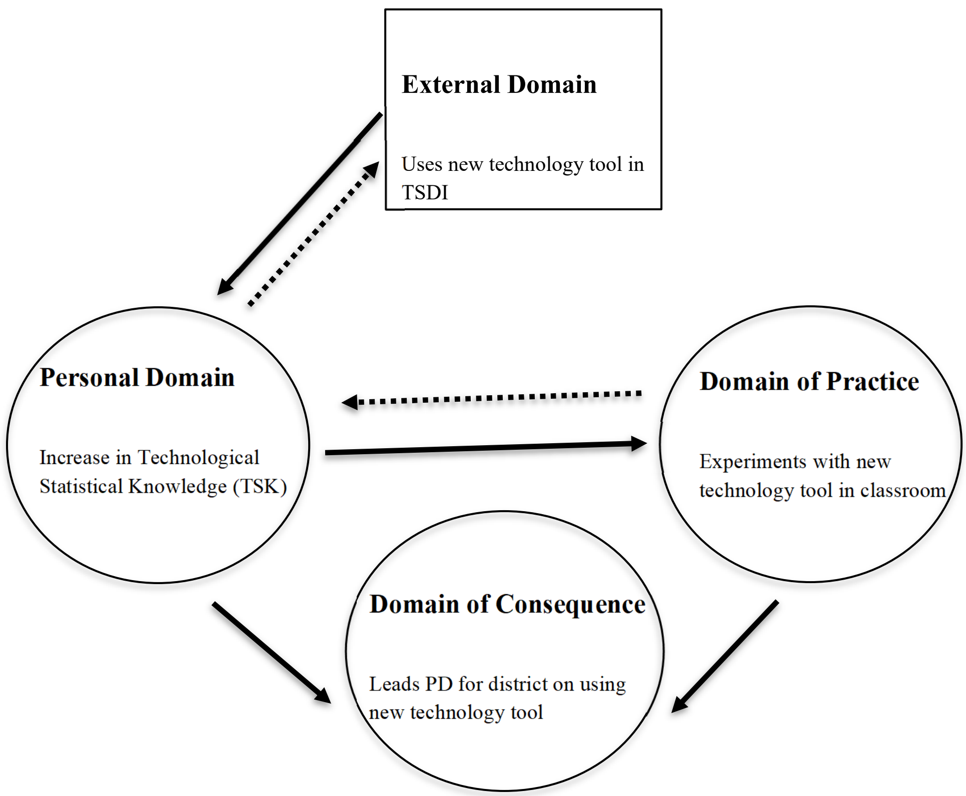
Clarke and Hollingsworth (2002) presented the IMPG to characterize the teacher change process domains (see Figure 1). In this model change occurs in "four distinct domains which encompass the teacher's world: the personal domain (teacher knowledge, beliefs, and attitudes), the domain of practice (professional experimentation), the domain of consequence (salient outcomes), and the external domain (sources of information, stimulus or support)" (Clarke & Hollingsworth, 2002, p. 950). The external domain is different from the other domains because it is not a part of the teacher's personal world. This model is cyclic with "enactment" and "reflection" connecting the four different domains.

Figure 1
The interconnected model of professional growth, from (Clarke and Hollingsworth, 2002, p. 951).



The interconnected model of professional growth is used to locate "change" that occurs in the three domain of the teacher's professional world (personal domain, domain of practice and domain of consequence). The professional growth of a statistics teacher who engaged in one of the statistics courses in this study could be described using the domains as follows (see Figure 2). Along this path of professional growth, he goes through cycles of reflection and enactment. A statistics teacher engages in a data investigation using a new statistics technology tool he has not encountered before (external domain). The teacher may learn to use the new statistics software that is presented in the course, increasing their own technological statistical knowledge (personal domain). He has time to reflect on what he has learned and decides to enact the use of the technology in his own classroom (domain of practice). After reflecting positively on his own experience with the tool, he then decides to enact by presenting the tool to colleagues. After using this technology in his classes for a couple of semesters, he decides to lead a workshop on using the statistics technology for other teachers in his district (domain of consequence).

Figure 2
Example of Professional Growth of a TSDI participant, solid arrows indicate enactment, dashed arrows indicate reflection



Prior TSDI and TSIR Research

The two online courses that are the focus of this study (TSDI and TSIR) were created to provide high quality online professional development for statistics educators. A more thorough description of the courses will be included in the methods section. The development team for the courses used the Interconnected Model of Professional Growth (IMPG) as a framework for studying the impacts of the course on participants' professional growth (Hollebrands & Lee, 2020). Prior research of these courses has focused on motivation and engagement of participants and the professional growth of participants for each of the domains in the IMPG (external domain, personal domain, domain of practice, and the domain of consequence). Since TSDI was released a full two years before TSIR, much of the research has focused on TSDI.

Motivation and Engagement of Participants

Since TSDI and TSIR provide participants the autonomy to engage with elements of the course however they desire to reach their goals, it is important for researchers to determine what motivates participants to enroll in a course. Avineri et al. (2018) and Tran and Lee (2016) found that participants in TSDI appreciated that they could engage with specific materials that could strengthen their understanding of content and pedagogy in areas that they were *personally* interested in improving. This section will present the prior research on motivation and engagement of participants of TSDI and TSIR.

Hollebrands and Lee (2020) analyzed participants in three online professional development courses for mathematics and statistics educators (two of which were TSDI and TSIR) offered between September 2015 and May 2019 (14 total offerings, 7 were TSDI and 4 were TSIR). They found that in the enrollment survey, of those that responded to a question asking about their reason for enrolling in the course, 44.8% enrolled to deepen their understanding of course content and 35.1% enrolled in the course to collect resources and tools to use in their own practice. Other motivating factors for enrollment have not been fully explored.

Click-log data from the courses has been analyzed to provide a rich description of how participants have engaged with the materials. Lee et al. (2017) and Mojica et al. (2018) used click log data to examine engagement trends in TSDI offerings. They found that participants that opened Unit 1 had a higher completion rate than traditional MOOC courses. Mojica et al. (2018) found that about 71% of those that engaged in the Orientation Unit went on to Unit 1, and of those 26% completed Unit 5.

Lee et al. (2018) found that despite being able to choose the order of engagement of the units in TSDI, there was little evidence of skipping units, and participants tended to progress linearly. Lee et al. (2017) looked at which units and elements of TSDI were accessed. They found that highest level of video engagement occurred in unit 3 of TSDI.

Tran and Lee (2016) analyzed click-log data from the Spring 2015 course offering to categorize participants into three categories. “No shows” were those that never entered the course after registration, “visitors” were those that logged in and engaged with materials four or fewer times, and “active participants” were the rest. Tran and Lee (2016) and Bonafini (2018) also acknowledged a group of participants identified as “lurkers”, those that read discussion forums but never actually posted to the forums. Though it has been hypothesized that lurkers probably gained something from participating in the courses, there has been no research to identify what they have learned in TSDI or TSIR.

Bonafini (2017) used click-log data to determine if engagement could predict completion rates. Bonafini found that the number of videos a participant watched throughout the course was not a predictor of completion rates, but the number of times a participant engaged in a discussion forum could be used to predict completion. Since a certificate of completion was earned by posting at least once in every discussion forum, this finding is not surprising.

Beyond engagement with materials, research has also focused on how participants in these courses engage with one another. Bonafini (2018) used the social theory of learning (Wenger, 1998) and connectivism (Siemens, 2004) to describe the nature of interaction between participants in the Fall 2015 TSDI course offering. Bonafini used social network analysis to characterize the interactions of participants in discussion forums. This analysis led her to identify 4 individuals identified as “super-posters”. There was a total of 2,095 posts generated by the participants of this course (excluding facilitators), and of those posts 10% were made by just these 4 super-posters (Bonafini, 2018). Though super-posters were helpful in furthering conversations in the forums, they were not considered “model” participants since only 1 of the 4 individuals was in the targeted K-12 teacher audience of the course. Barker and Lee (2018) identified a group of eight highly active participants that took TSDI and TSIR in succession. These participants were leaders in discussions and helped further the topics in the forums where they posted.

During the Fall 2016 and Spring 2017 TSDI course offerings, professional learning teams (PLTs) were formed among participants that met regularly to discuss the materials (Akoğlu, et al., 2019). Nine teams were formed, with 8 meeting face to face and 1 meeting virtually. Akoğlu (2018) investigated the professional growth of these participants as they interacted online with other participants and within their PLTs. The participants who took part in a PLT were also very active in engaging with materials throughout the course. These interactions had a positive impact on what they learned about teaching statistics (Akoğlu et al., 2019).

External Domain

Recall that in the interconnected model of professional growth there are two types of domains, those that are inside the teacher's professional world (personal domain, domain of practice, and domain of consequence) and the external domain which is outside the teacher's professional world (Clarke & Hollingsworth, 2002). For this study, the external domain will be defined as the online professional development courses, TSDI and TSIR. The external domain includes the resources available in the courses as well as the interactions that occur in that learning space. First, I will present studies that have elaborated on the design of the courses, i.e., external domain. The following sections will explore the research that has been done to determine what effect this external domain has had on the three other domains of the IMPG.

Bonafini (2018) compared the features of the TSDI course to characteristics described in the literature for effective face-to-face teacher PD. In the literature she found, Bonafini identified three fundamental features of effective PD as being content focused, having opportunities for active learning, and coherence. The three structural features for effective PD are types of activities, duration, and collective participation. Though the comparison of effective face-to-face PD showed that the features of TSDI were not identical to those in the literature, the features were evident and modified by the constraints and possibilities of OPD.

The TSDI and TSIR courses were created by teams at the Friday Institute for Educational Innovation at NC State University using research-based design principles of effective PD and online learning which focus on four principles: a) self-directed learning, b) peer-supported learning, c) job-connected learning and d) learning from multiple voices (Kleiman et al. 2014). Much of the previous research has explained how these four principles are enacted throughout the design of the courses (Lee & Stangl, 2015; Tran & Lee, 2016; Lee et al., 2018; Hollebrands & Lee, 2020). These courses support self-directed learning by offering participants a variety of materials that they can engage with how they see fit. Peer-supported learning is evident in the unit sections where participants can engage in discussion forums together. Both courses provide experiences for participants to engage in a statistical data investigation like how their students would, which is an example of job-connected learning. Learning from multiple voices is evident in the videos available where participants can experience examples of best practices that they can consider when incorporating statistics into their own classrooms. Participants also get a chance to watch interviews of statistics educators about issues they may encounter in their own classes.

Personal Domain

The effect the external domain of engaging in TSDI and/or TSIR has had on the personal domain of teachers of statistics has been a focus of research. Tran and Lee (2016) and Lee et al. (2017) identified the external domain of participants of TSDI as the materials and resources in the OPD as well as the interactions of participants in the discussion forums. The personal domain was identified as participants' knowledge and beliefs, specifically about teaching statistics. Lee et al. (2017) sought to identify "triggers" in the external domain that had an impact on changes in the personal domain in one course offering of TSDI. Elements identified as triggers for critical reflection that had an impact on participants' beliefs and perspectives included resources that supported the SASI framework, videos featuring discussions with a panel of experts in statistics education, videos of students and teachers engaged in statistical investigation tasks and using technology to visualize real, multivariable, and messy data. Teachers' beliefs and perspectives changed in a variety of ways including “engaging in statistics is enhanced using dynamic technology” and “statistical thinking develops along a continuum” (Lee et al., 2017, p. 412).

Mojica et al. (2018) extended the Lee et al. (2017) study to investigate six course offerings of TSDI between Fall 2015 to Fall 2017. They extended the list of major themes of changes in beliefs and perspectives about teaching statistics from four themes to eight themes. Akoğlu (2018) used the triggers identified by Lee et al. (2017) as a basis for identifying “lived experiences” of participants in the TSDI course and a PLT. Examples of lived experiences include learning about and engaging with real and messy data, learning about and engaging with technology and sharing about personal practices. It was shown that these lived experiences had a positive impact on participants’ beliefs and perspectives about teaching statistics.

Domain of Practice

Prior research has found that participants have changed or intend to change their teaching practices after engaging in the OPD of the two courses of this study. Tran and Lee (2016) analyzed open responses on surveys and replies to discussion forum prompts to describe a shift in some participants’ approaches to teaching statistics based on what they had learned in TSDI. For instance, participants stated that being introduced to the SASI framework was one of the most influential parts of the course, and they had intended to incorporate it into their planning process for teaching statistics. Discussion posts in which educators included topics on experimenting with new ideas in their classroom were the ones that seemed to attract the most interest among participants (Hollebrands & Lee, 2020; Lee et al., 2020).

Mojica et al. (2018) analyzed responses from the end-of-course survey as well as a follow up survey sent out 6 months after course completion. Many participants responded in the end-of-course survey that they had used or intended to use many of the activities as well as dynamic statistical software that was introduced in TSDI. The follow up survey indicated that 63% of respondents had applied the knowledge and skills acquired in TSDI to their own practice.

Despite evidence of teachers intending to change their teaching practices, there is not substantial evidence of the long-term effect that participation in these courses has had on participants' domain of practice. Akoğlu (2018) intended to collect tasks from a subset of participants to evaluate the evidence of the impact of TSDI on practice. Due to a low number of task submissions, he did not include them in his study. Though many of the studies provided implied evidence of changes to teaching practice, there is common agreement that collecting artifacts of practice, conducting interviews or conducting classroom observations would provide stronger evidence of change in teaching practice (Akoğlu, 2018; Hollebrands & Lee, 2020; Lee et al., 2020).

Domain of Consequence

Evidence of a change in the domain of consequence of TSDI and TSIR participants has not been a focus of research. The domain of consequence is described as "salient outcomes" in the IMPG (Clarke & Hollingsworth, 2002). In describing teacher change, salient outcomes are often tied to innate changes in a teacher's value system. For instance, a teacher experiments with implementing data investigations into their class (domain of practice) and notices that students respond positively to the new practice (reflection). The teacher then makes using data investigations a regular part of her practice after realizing the value this practice has on student outcomes (domain of consequence).

Akoğlu (2018) included in the domain of consequence a "perceptual change in classroom practice" (p. 50) and "teachers' salient adaptation of new methods in their teach[ing] practices" (p. 51). He hypothesized that these salient outcomes would occur for participants in TSDI but observing it would require observation of teachers' practices which was outside of the scope of his study. I also could not observe teachers' practices in this study, but I do believe that evidence of this can be found through surveys, teacher interviews and collecting teaching artifacts several years after teachers have engaged in either or both courses. Mojica et al. (2018) found that in a follow-up survey given 6 months after participation in TSDI, many of the participants stated in open-ended responses that they are creating tasks and planning lessons based on what they had learned in TSDI. Not only did some participants experiment with the ideas (domain of practice) they are *still* using those ideas in their current practice (domain of consequence).

Another salient outcome that could provide evidence of change in the domain of consequence is participants' desire to share the knowledge they gained with others. If a participant has embraced the ideas of the courses in their own practice so innately that they want to share it, then it must be a lasting salient outcome of their participation. The lead instructor of TSDI has said that participants have reached out to her to discuss their plans of using TSDI resources in PD. For instance, "a participant from Honduras translated several key resources to Spanish and used them in professional development with teachers" (Lee & Stangl, 2017, p. 8). One of the participants in Akoğlu's (2018) study decided to lead a PLT of teachers taking TSDI, after having a positive experience taking the course the previous semester. I believe that evidence of others having similar experiences will emerge through another follow up survey.

Recommended Next Steps for TSDI and TSIR Research

The previous sections provided a summary of prior research of participants' motivation and engagement while taking TSDI and/or TSIR as well as evidence of change using the IMPG as a framework. Research has been centered around exploring engagement trends of participants while taking the courses as well the effect the external domain has had on the personal domain of teachers. Though the amount of research that has been done in the five short years since the first course offering of TSDI has been impressive, the large amount of available data and the questions that remain unanswered about participation in the courses calls for further research.

Though research on engagement and motivation exists, I believe there is more to be explored. Motivation has been touched on by looking at responses to the enrollment survey (Hollebrands & Lee, 2020). Next steps should include how motivation drives engagement. Research has identified groups of participants by their engagement, i.e., lurkers, super-posters, active participants (Barker & Lee, 2018; Bonafini, 2017; Tran & Lee, 2016). But I believe cluster analysis may be a more effective tool in identifying groups of individuals based on their motivation for enrollment and engagement with materials over time (Frankowsky, et al., 2015).

In using the IMPG to describe the professional growth of participants, I feel that examining the effect the external domain has on the personal domain of participants has been thoroughly explored. Research has already explored the external domain of TSDI and what makes it a unique online learning experience (Bonafini, 2018; Hollebrands & Lee, 2020; Lee & Stangl, 2015; Lee et al., 2018; Tran & Lee, 2016). Though this sort of analysis has not been done for TSIR, I feel that providing a similar analysis would look almost identical to this previous research since the leaders for the design team of the courses were the same. Identifying triggers in the external domain of TSDI that causes a change in the personal domain was first explored by

Lee et al. (2017) then expanded on by Mojica et al. (2018) and Akoğlu, (2018). Though TSIR has different goals than TSDI, I believe similar triggers would emerge that have been seen in this prior research. Many of the triggers are elements that exist in both courses, such as *expert panel video discussions* and *videos of students and teachers engaged in statistics tasks*. It would not be surprising to find these same things that caused a change in the personal domain of participants of TSDI would be the same as TSIR.

Future research should focus on exploring the change that occurs in the domain of practice and the domain of consequence. Prior researchers have stated that more evidence of a change in practice should be collected, such as teaching artifacts, classroom observations, and follow-up interviews (Akoğlu, 2018; Hollebrands & Lee, 2020; Lee et al., 2020). Previous studies have only been able to show evidence for *intended change in practice*, further research may be able to support *actual changes in practice*. Evidence for salient outcomes in the domain of consequence could also be found through a follow-up survey given over a year after the last course offering, as well as selected follow up interviews. Perhaps the different ways that participants are motived and engaged in the courses has an influence on the change they experience in these different domains.

Clarke and Hollingsworth (2002) explain how the IMPG can be used to describe the "path" individuals take during professional growth. Akoğlu (2018) described several constructs of one domain to another and hypothesized on how those constructs may be enacted. He used these constructs to guide his analysis. In his research he was able to explore in depth the constructs of *External domain >> Domain of Practice* and *External Domain >> Personal Domain*. I believe that the IMPG can be used to explore the paths individuals take using the domains as described by Clarke & Hollingsworth (2002). Instead of only looking at constructs from one domain to the other, perhaps through interviews, a more complete picture of individuals' lived experiences can be visualized in all the domains.

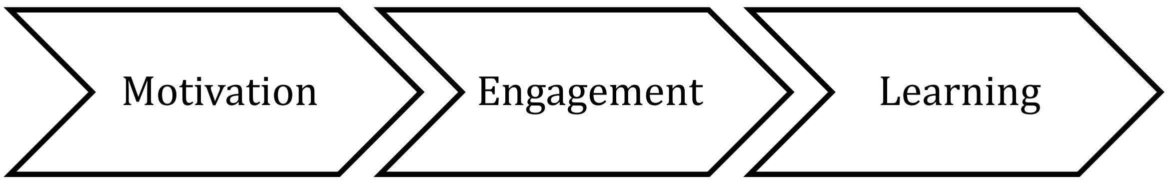
Framework

This section will describe a model of motivation, engagement and professional growth that will be used for my research. I use the model of engagement shared by Wiebe and Sharek (2016) to situate my research. The general model of engagement situates engagement between motivation and learning. For my model instead of situating engagement between motivation and learning in a linear order, I propose that motivation and engagement can lead to professional growth in the cyclical IMPG framework. My research will use the IMPG to situate professional growth, specifically in the domains of practice and consequence.

General Model of Engagement

Wiebe and Sharek (2016) state that there is no one unified model of engagement, but they explore many well-established psychological models that have been used to understand engagement. Each of these models is linked to a sequential model they call the *General Model of Engagement* (see Figure 3). This model shows that engagement is at the center of motivation and learning. To understand engagement, we must first understand the goals and decisions that bring individuals to the point of engaging in effortful tasks, such as engaging in OPD.

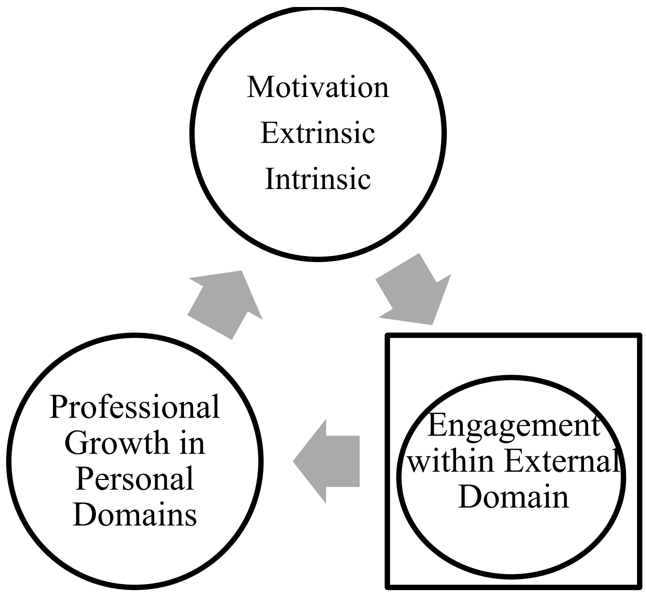
Figure 3
General Model of Engagement (Wiebe & Sharek, 2016)



Conceptual Framework

Here I will describe the conceptual framework that I will use to situate my study. Instead of a linear model of engagement as shown in Figure 3, I propose a cyclic model of motivation, engagement and professional growth for participants of statistics OPD courses (see Figure 4). The general model of engagement is limiting because it seems that there is an endpoint to the learning process. I propose that motivations can arise *again* after change has occurred in the personal domains of professional growth (personal domain, domain of practice, and domain of consequence). In the specific case of participants in TSDI and TSIR, I hypothesize that there will be participants who experience professional growth after engaging in the external domain of TSIR, then are motivated by that growth to enroll in TSIR. There may also be individuals who participated in one of the courses minimally, then decide to re-enroll to participate more fully, thus changing their patterns of engagement in the external domain. There may be many motivating reasons for entering the cycle again.

Figure 4
Model of Motivation, Engagement, and Professional Growth for Participants of OPD Courses



Before choosing to engage in a professional learning experience, a participant must have some sort of motivation to begin the learning experience. Motivations can be classified as extrinsic or intrinsic motivations. Depending on the participant, extrinsic and intrinsic motivations can take different forms. Extrinsic motivation may be the desire to get a certification for PD hours (Moore & Wang, 2020; Wilkowski, et al., 2014) or to have social interactions with others engaged in a course (Moore & Wang, 2020; Wiebe & Sharek, 2016). Intrinsic motivations may be internal factors for enrolling in a course such as increasing knowledge (Hollebrands & Lee, 2020) or self-efficacy for a subject.

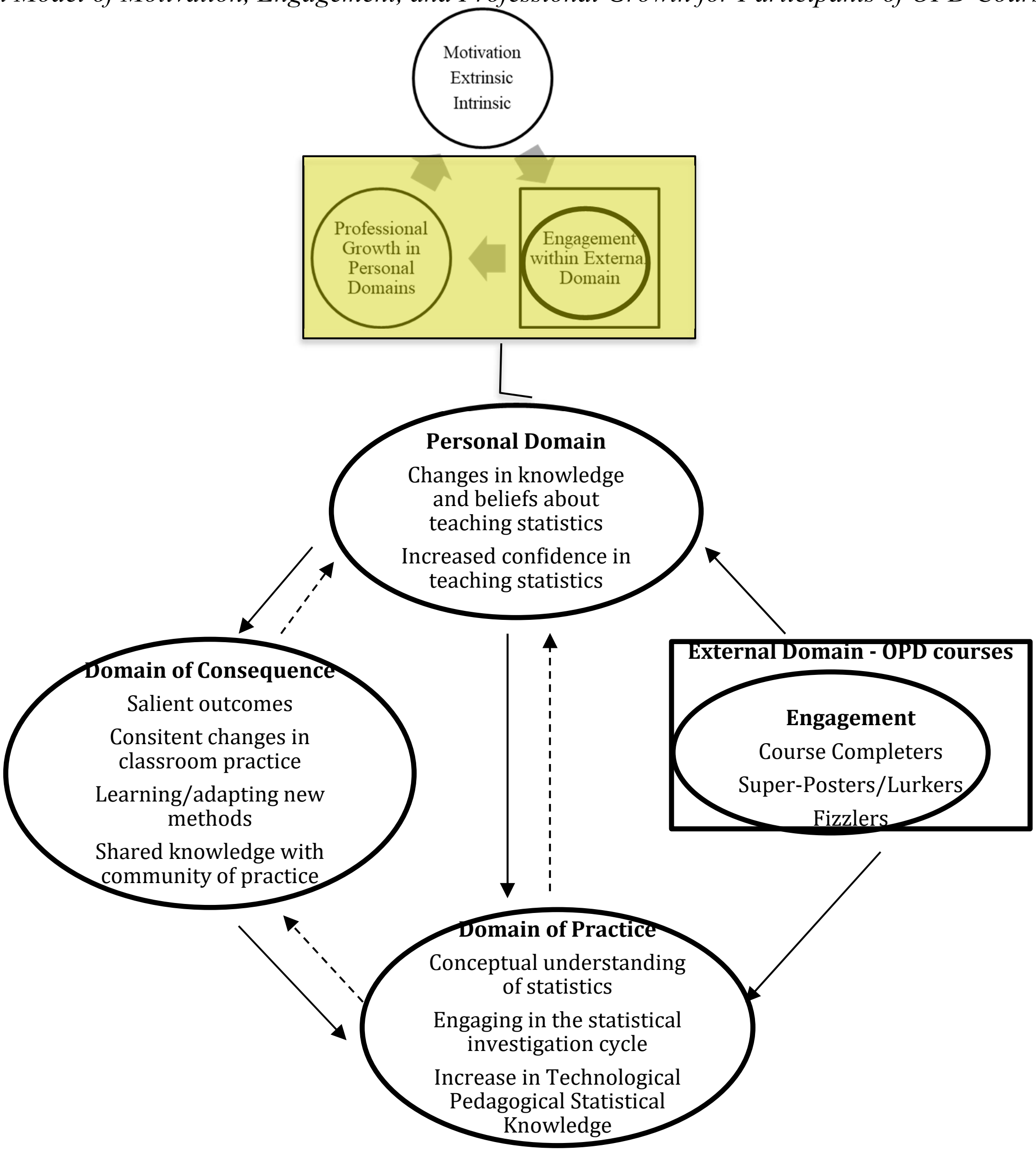
The elements of the cycle that are part of the participant's personal world (motivation, engagement, professional growth in personal domain) are in circles whereas the external domain is a square. The elements that are circles will be where change can occur, whereas the square (the external domain of the courses) will not change. I hypothesize that patterns of engagement may change for participants who participated in both courses and even participants that may have enrolled more than once in the same course. For this reason, I decided to represent engagement as a part of the participant's personal world, which may possibly change, within the external domain which is outside of the participant's personal world.

The professional growth of participants in OPD for statistics educators is highlighted and expanded on in Figure 5. Engagement in the external domain of the courses can lead to changes in these domains. As described previously, engagement in online learning can be described in many ways. Participants may have completed all parts of the course to earn a certificate of completion (Bonafini, 2017) or engaged in the course early on and "fizzled" out towards the end of the course (Frankowsky et al., 2015). Participation in discussion forums is the main source of participation in these courses. Discussion posters may be super-posters, taking the lead in discussions (Bonafini, 2018), or lurkers who view all the discussion posts but never make their own post (Bonafini, 2018; Nandi, et al., 2009).

Change in the personal domain can be characterized by changes in knowledge and beliefs and increased confidence in teaching statistics. Prior research has described positive changes in knowledge and beliefs about teaching statistics for participants of TSDI (Akoğlu, 2018; Lee et al., 2017; Mojica et al., 2018). These changes include realizing the importance of using dynamic technology, the importance of using real and messy data in statistical investigations, and statistical thinking and mathematical thinking involve different processes (Mojica et al., 2018). Evidence has also shown that participation in TSDI has increased participants' confidence to teach statistics (Lee et al., 2020). Though prior research has focused on changes in knowledge and beliefs for participants of TSDI, I believe similar themes would arise for participants in TSIR.

Figure 5

Extended Model of Motivation, Engagement, and Professional Growth for Participants of OPD Courses



Reflecting on (dotted lines) or enacting (solid lines) the material learned in the external domain can have a change on the domain of practice and the personal domain. PD that has focused on conceptual understanding of statistics (Peters et al., 2014; Peters & Stokes-Levine, 2019) has shown an increase in knowledge and understanding, though there has not been much research on if teachers are using conceptual understanding in their own practice. There has also been evidence of change in knowledge and beliefs about engaging in the statistical investigation cycle (Dolor & Noll, 2015; Lee et al., 2020; McClain, 2009). It has been found that teachers *intend* to change their practice by incorporating more statistical investigations (Akoğlu, 2018; Mojica et al., 2018), though evidence of actual change still needs to be done. Change in the way participants incorporate technology should also be investigated when describing professional growth. Though many participants of PD for teachers of statistics find dynamic statistical software useful in understanding statistical concepts (Madden, 2014; Lee et al., 2020; Wassong & Biehler, 2014), there still exists barriers for teachers to use this technology in their own classrooms (Lee & Nickell, 2014; Lovett & Lee, 2017).

Changes in the personal domain and domain of practice can lead to change in the domain of consequence. I am interested in describing sustained changes in salient outcomes which can include sustained changes to practice, continual adaptation of new methods, and shared knowledge with a community of practice. Evidence for these outcomes could include participants engaging in other PD intended for statistics educators (Garfield & Everson, 2009) or influencing others to engage in similar PD (Akoğlu, 2018; Lee & Stangl, 2017). The model of motivation, engagement, and professional growth for OPD courses (Figure 5) can be used to describe the path of the changes of participants or groups of participants over time.

CHAPTER 3 METHODS

Prior to analyzing the professional growth of educators who engaged in the online courses for statistics educators, motivations for enrollment and patterns of engagement in the online environment were identified. The way that educators engage in online professional development (OPD) depends largely on the way the OPD is organized. For instance, hybrid PD combines traditional face to face PD with online learning opportunities, such as participating in ongoing online discussion boards (King, 2002). Synchronous OPD provides opportunities for people to meet at the same time for PD in an online environment, even when they are not able to share the same geographic location (Annetta & Shymansky, 2006; Francis & Jacobsen, 2013). Asynchronous OPD also exists that has participants interact with materials online and complete certain requirements on their own time (Hill et al., 2013).

I was interested in grouping participants of OPD for statistics educators by their motivations for enrollment and the behaviors or characteristics they exhibit while engaging in OPD. Researchers have concluded that finishing a MOOC or earning a certificate of completion is not the only way to define *success* in these online courses (Frankowsky et al., 2015; Wilkowski et al., 2014). Being able to describe participants professional growth after engaging in TSDI or TSIR will be a better way to analyze the *success* of participants. I hypothesize that the way different groups of participants engaged in the courses will influence the professional growth they exhibit.

The research questions that guide this study:

1. How can participants across two online professional development courses for teachers of statistics be characterized based on their motivation for taking the course(s) and their engagement during the course(s)?

a. What motivates participants to enroll in online professional development courses for statistics educators?

i. In what ways can topic modeling be an effective tool to identify motivation of participants who enroll in online professional development courses for statistics educators?

b. How do participants of OPD for statistics educators engage in the courses?

c. How is motivation for enrolling in OPD for statistics educators related to how participants engage in the course(s)?

2. How did participation in statistics education online professional development impact ongoing professional growth of participants?

Study Context

This study is bounded by the online environment of two successive OPD courses, Teaching Statistics through Data Investigations (TSDI) and Teaching Statistics through Inferential Reasoning (TSIR), and educators who choose to participate in the course(s). These courses are hosted by the Friday Institute for Education Innovation through their learning platform, The PLACE: Professional Learning and Collaboration Environment. The PLACE is a website (place.fi.ncsu. edu) that provides free resources to educators for professional development, including MOOC-Eds, blending learning opportunities, micro-credentials, and teaching resources. The materials found at The Place were developed by researchers that work at The Friday Institute, a research center that is part of the College of Education at North Carolina State University. The MOOC-Ed courses at the Friday Institute are partially funded by the William and Flora Hewlett Foundation. The course development teams for TSDI and TSIR were led by Dr. Hollylynne Lee, a Professor of Mathematics and Statistics Education in the department of Science, Technology, Engineering and Mathematics Education at NC State University.

Description of Courses

The "overarching goal of [TSDI] is to engage participants in thinking about statistics teaching and learning in ways that are likely different from their current practices in middle school through college-level introductory statistics" (Lee, et al, 2020, p. 4). Participants in the course were introduced to the Students Approaches to Statistical Investigations (SASI) framework, which incorporates the four phases of the statistical investigation cycle (pose, collect, analyze, interpret), statistical habits of mind, and different levels of statistical sophistication (Lee and Tran, 2015). The course consisted of 5 units and an orientation unit (see .

Table **1**). Each of the 5 units after the Orientation unit in TSDI included 7 sections followed by a Unit Feedback Survey.

Table 1
Teaching Statistics through Data Investigations (TSDI) Outline (TSDI, n.d.)

Unit	**Summary**
0: Orientation	During *Orientation* you will meet your lead instructor and learn what to expect from the Teaching Statistics MOOC-ED.
1: Considering the Possibilities of Teaching Statistics with Data	*Considering the possibilities of teaching statistics* with data focuses on what statistics is and why it is taught in schools. This unit explores the possibilities of students engaging with real data and cool tools and of teaching statistics with data.

Table 1. (continued)

2: Engaging in Statistics	*Engaging in Statistics* takes a careful look at what it means to engage in statistics. This includes examining the difference between mathematics and statistics, learning the statistical investigation cycle, and considering habits of mind when working with data, and watching as a teacher engages students in a statistical investigation.
3: Introducing Levels of Statistical Sophistication	*Introducing levels of statistical sophistication* explores a framework for supporting growth in students' statistical sophistication and digs deeper into statistical habits of mind. You will learn about a statistical task framework to design, adapt, and analyze instructional tasks and explore students' levels of statistical sophistication.
4: Delving Deeper into the Investigation Cycle	*Delving Deeper into the Investigation Cycle*, provides teaching and learning materials to assist you in understanding the different components of a statistical investigation, including several resources that can be used directly with students.
5: Putting It All Together	*Putting it All Together* considers how to change teaching practices that can really engage students in doing statistics with real data.

TSIR also was intended to attract educators in middle grades to college, interested in strengthening their statistics pedagogy. This course was meant to be an extension of the materials in TSDI while emphasizing inferential reasoning. TSIR introduces participants to the Inferential Reasoning Task (IRT) guidelines as well as other resources and strategies to consider when incorporating inferential reasoning into their statistics courses. The Orientation unit in TSIR included a review of topics covered in TSDI. The remaining 5 units in TSIR include 5 sections followed by a Unit Feedback Survey (see Table 2).

Table 2
Teaching Statistics through Inferential Reasoning (TSIR) Outline (TSIR, n.d.)

Unit	Summary
0: Orientation and Review of SASI Framework	In Orientation, you are introduced to the course and colleagues, and can review essential background material related to a framework for supporting Students' Approaches to Statistical Investigations (SASI).
1: What is Inferential Reasoning?	In this unit, you learn core aspects of inferential reasoning, why it is important in statistics, and how it develops, from informal approaches with early learners to more formal approaches as learners get more sophisticated, as described in the SASI framework.
2: Inferential Reasoning with Comparing Groups	In this unit, we take a deep dive into questions that provide opportunities for learners to compare two or more groups.
3: Inferential Reasoning Between Samples and Population	Generalizing from a sample to a population is often considered the quintessential way to make inferences in statistics.
4: Inferential Reasoning with Competing Models	This unit focuses on how learners can engage with questions that focus on making decisions about which model is the most plausible for describing a population.
5: Making Inferential Reasoning Essential in Your Practice	This unit will assist you in making plans to change teaching practices that can really engage students in inferential reasoning. You will reflect on, assess, and share what you have learned throughout the course.

TSDI was taught seven times through The PLACE, with the first offering in the Fall of 2015 and the last in the Fall of 2018. [TSDI was offered in Spring 2015 through another platform and then drastically revised for Fall 2015.] TSIR was offered three times, in Fall 2017, Spring 2018 and Spring 2019. The courses were asynchronous, meaning that participants were able to complete course work at their convenience; they were not required to log in to the course at a pre-determined time.

In Fall 2015, the materials for TSDI were released by the instructor gradually, usually one unit a week, but participants had the entire time the course was open to complete the materials. Starting in Spring 2016, all units of TSDI were available when the course opened, and participants could complete the course at their own pace. When TSIR was released in Fall 2017 all units were available. Though participants could navigate to each unit in any order, all sections of the unit were not available until the first section of each unit had been accessed. Each course was open for approximately 10-15 weeks. If participants completed the course requirements, they earned a certificate of completion that satisfied 20 hours of continuing education credits. Though participants were encouraged to complete TSDI before TSIR, it was not required.

Each unit contained different sections that are described in Table 3 and Table 4. To obtain a certificate of completion, participants had to access and engage with all materials in *Engage with Essentials,* complete all activities and engage in the discussion forum in the *Investigate (TSDI)* or *Explore and Discuss (TSIR)* section, and post at least once in the *Discuss with your Colleagues* forum for Units 1 – 5, as well as complete the end-of-course survey. There was a total of 11 discussion forums in each course, which includes an introductory forum to meet fellow participants. Participants had the option to start a new thread in each discussion forum or to reply to previous posts. Dates and times are given for the latest post so that participants can determine if a discussion is still active. There is no limit to how many times participants can post to a forum.

Table 3
Description of each section of Teaching Statistics through Data Investigations (TSDI)

Section	This section included...
Engage with Essentials	…readings and videos that were created by the course design team or curated from open online resources. Each unit included videos of students and teachers engaging in statistics in the classroom
Learn from our Expert Panel	…a video of the instructor and 3 experts in statistics education engaging in a discussion relevant to the subject of each unit.
Dive into Data	…an opportunity for participants to explore a data set using different statistical technology tools such as Gapminder, TUVA, CODAP, and Statcrunch.
Investigate	…a statistics investigation task unique to each unit. This section gave participants an opportunity to engage in the statistics task as a student would, watch a video of students engaging in the task, then participating in a discussion forum with other participants about this experience.
Discuss with your colleagues	…an open-ended discussion forum for participants to discuss what they have learned in the unit
Extend your Learning	...a list of resources for further exploration of the topics in the unit
Participate with a Project (*included in Fall 2015, Spring 2016, Summer 2016 iterations*)	… the opportunity for participants to create and implement a lesson based on what was learned in that unit, then share it with others through a discussion forum.
Demonstrate your Learning (*included in Fall 2016, Spring 2017, Fall 2017, Fall 2018 iterations*)	… links for participants to complete microcredentials that could be completed based on what was learned in the unit. The microcredentials were created by the course development team as another way to earn CEUs without completing the entire course. There are six microcredentials, each worth between 5 – 7.5 hours of credit per successful completion.

Table 4

Description of each section of Teaching Statistics through Inferential Reasoning (TSIR)

Section	This section included...
Engage with Essentials	…readings and videos that were created by the course design team or curated from open online resources. Each unit included videos of students and teachers engaging in statistics in the classroom. This section also includes a video of the instructor and 3 experts in statistics education engaging in a discussion relevant to the subject of each unit.
Learn from Practice	…a *Teacher Talk* video which features a conversation with statistics educators about their experience with the topics in each Unit. This section also includes an *Inside the Classroom* video of actual students or an animation of students engaging in a statistical investigation.
Explore and Discuss	…an opportunity for participants to explore a data set using different statistical technology tools and an investigation task unique to each unit. This section gave participants an opportunity to engage in the statistics task as a student would, watch a video of students engaging in the task, then participate in a discussion forum with other participants about this experience
Discuss with your colleagues	…an open-ended discussion forum for participants to discuss what they have learned in the unit
Extend your Learning	...a list of resources for further exploration of the topics in the unit

Participants

Participants for this study are the individuals that participated in at least Unit 1 of either TSDI and/or TSIR. The free courses were "advertised through websites and listservs of many different educational organizations (NCTM, ASA, CAUSEweb, IASE), social media posts, emails to past participants in any MOOC-Ed, state-level leaders in mathematics education in the U.S., and personal contacts" (Lee et al., 2020, p. 7). There are several individuals who registered for course(s) but did not access any of the materials. Hollebrands and Lee (2020) investigated three courses offered by the Friday Institute (TSDI, TSIR, and another MOOC for educators) and found that across all courses, roughly 40% of participants who accessed Unit 1 completed the course through Unit 5. Hollebrands and Lee did not include those registrants that had accessed the Orientation Unit but not Unit 1 in their study, assuming those individuals realized the "course was not of interest to them, or those who determined they did not have the time to engage further" (p. 6). Similarly, for this study I only included those participants who accessed at least Unit 1 of either course.

In the seven offerings of TSDI there were a total 3,115 participants registered for the course. In the three offerings of TSIR there were a total of 700 participants registered for the course. The primary audience for TSDI and TSIR are grade 6-12 teachers and post-secondary teachers who teach statistics. The courses can also be of interest to elementary teachers, teacher educators, and teachers of other disciplines. Both courses have drawn a variety of participants with a variety of different backgrounds, though most participants are classroom instructors. Lee et al. (2020) examined the impact of participating in TSDI had on the beliefs and perspectives about statistics on the participants personal domain. For that study, Lee et al. focused on K-12 classroom teachers who participated in TSDI during Fall 2015. Since I am interested in how the external domain of the courses affects any of the participants, I included *all* participants who accessed at least Unit 1 of either course, not just those who indicated they were classroom teachers.

Study Design

A sequential mixed methodology approach was used for the design of this study, in which a phase using qualitative methods is built upon a phase using quantitative methods

(Creswell et al., 2003; Ivankova et al., 2006; Ivankova, 2014). An example of a sequential mixed methodology could use the following procedures: quantitative data collection, quantitative data analysis, connecting quantitative and qualitative phases, qualitative data collection, qualitative data analysis, and integration of quantitative and qualitative results (Ivankova et al, 2006). The following sections will detail how my study incorporated these features. Though this study design can provide rich results, the biggest drawback is that the time required to collect and analyze data can be lengthy since the data required for the second part of the study often cannot be collected or analyzed until the first part of the study is complete (Ivankova et al., 2006).

The first phase of the study used data already collected during course registration, discussion forum posts and click log data. Only data from those participants that accessed at least Unit 1 were included in the analysis. Cluster analysis was used to group participants based on their patterns of motivation and engagement. Cluster analysis is an exploratory technique that is useful in characterizing patterns in data when initial groupings are not known (Gareth, et al., 2017). The second phase of the study analyzed ongoing professional growth of participants through a follow-up survey. Unfortunately, the survey response was very low, so I was not able to collect a lot of data for the second phase. This will be expanded on in Chapter 7.

Since the ways that a participant may engage in the courses or decide to enroll in a course is so varied, the first step of the study grouped participants based on motivation and engagement. Many researchers do a cross case analysis by forming *types* or *families* that share certain patterns or characteristics (Miles et al., 2014). Cluster analysis has been used by other researchers to group participants of MOOCs based on motivation and engagement (Frankowsky et al., 2015; Thompson et al., 2016; Wiebe & Sharek, 2016). The groups are formed will answer the first research question - *How can participants across two online professional development courses for* *teachers of statistics be characterized based on their motivation for taking the course(s) and their engagement during the course(s)?*

This first research question has two sub questions. The first sub question (*What motivates participants to enroll in online professional development courses for statistics educators?*) will be answered using clusters that are formed from motivation data. This data includes answers to the enrollment survey as well as themes for motivation that arose from topic modeling. These themes answer another sub question, *in what ways can topic modeling be an effective tool to identify motivation of participants who enroll in OPD courses for statistics educators?* After clusters were formed based on motivation, I used click-log data collected from participants while they took the course to form clusters of participants based on engagement. This answer the next sub question, *how do participants of OPD for statistics educators engage in the courses?* I then combined the motivation and engagement cluster results to answer the last question, *how is motivation for enrolling in OPD for statistics educators related to how participants engage in the course(s)?*

The second phase of the study included a survey sent to participants of TSDI or TSIR that accessed at least Unit 1 of at least one course. Survey responses were analyzed to identify changes specific to the personal domain, domain of practice and domain of consequence of the IMPG. I investigated the overall themes in the change of these domains. These results will answer the second research question *how did participation in statistics education OPD courses impact ongoing professional growth for participants?*

Phase 1: Cluster Analysis using Motivation and Engagement Factors

Statistical analysis tools can be classified into two broad categories, supervised learning and unsupervised learning. Supervised learning includes analysis methods such as regression and classification. The goal of supervised learning is often to predict some response variable, for a set of *n* observations, from a known set of features. Unsupervised learning uses a set of features for a set of *n* observations to determine interesting patterns, visualize the data, or perhaps to determine subgroups based on features of the data (James et al., 2013). Bonafini (2018) used supervised learning methods to determine which features of participants in TSDI could be used to predict completion rates. Instead of using features of participants to *make predictions*, I used unsupervised learning methods, cluster analysis, to *group participants* by features based on motivation and engagement.

Clustering techniques include a large set of methods that can be used to find clusters or subgroups in a dataset. When clustering techniques are used on a set of participants "we seek to partition them into distinct groups so that observations within each group are quite similar to each other, while observations in different groups are quite different from each other" (James et al., 2013, p. 385). Other researchers that have analyzed motivation and engagement of MOOC-Ed participants have used hierarchical clustering (Frankowsky et al., 2015) and latent profile analysis (Moore & Wang, 2020; Wiebe & Sharek, 2016; Thompson et al., 2016) to form groups. For my study I went through several clustering methods, including hierarchical and latent profile analysis, before deciding that a k-means clustering algorithm, which is an example of a centroid-based clustering method, was best (see Chapter 5). The following sections include the sources of data that will be used to generate the features for cluster analysis and general steps for cluster analysis.

Sources of data for cluster analysis

To perform cluster analysis, each of the participants were assigned a set of features associated with them. These features were grouped by motivation and engagement. Cluster analysis was used to group participants by the features that are most likely associated together. This section will describe how the features for motivation and engagement were identified for each participant.

Two sources of data were used to identify participant motivation for enrolling in the courses; the enrollment survey and the *Meet Your Colleagues* discussion forum for each of the courses. When participants registered for TSDI and TSIR they filled out an enrollment survey (see Appendix A and B) that included the question "Which of the following best describes your primary reason for enrolling in this course?" with the following options: *Just browsing, Deepen my knowledge of the course topic(s), Connect with peers/colleagues, Collect resources and tools for my practice*, or *Earn a certificate of accomplishment/renewal credits*. Participants' choices were used as one feature for grouping them via cluster analysis.

In addition to classifying motivations from the enrollment survey data, the initial *Meet Your Colleagues* discussion forum provided rich, finer grain details of participant motivation. This forum asks participants to share a little about themselves and share why they are interested in taking the course. After isolating the discussion posts made by those participants who accessed at least Unit 1, I used topic modeling in R to analyze the posts. Topic modeling is a method that can be used for classification of large groups of texts into discrete groups of words (Silge & Robinson, 2019). Topic modeling identified groups of words based on the frequency with which they appear with other words. The methods for the topic modeling approaches will be discussed in their entirety in Chapter 4.

Click-log data for each participant was collected and organized to describe engagement for each participant. Lee, Mojica, and Lovett (2020) studied the impact participating in TSDI had on a subset of K-12 classroom teachers' beliefs and perspectives about teaching statistics. In that study, Lee et al. (2020) described how teachers participated in the course and engaged with materials using click-log data. This data was used to show the percentage of participants who accessed each unit. Lee et al. (2020) also tallied the frequency of posts to discussion forums of these classroom teachers to illustrate engagement. I similarly used click-log data over time as features to use for cluster analysis. The categories of click-log data and data cleaning methods will be further discussed in Chapter 5.

General procedures for cluster analysis

Battaglia et al. (2016) discuss the application of using cluster analysis in the field of education. They describe a general procedure for performing cluster analysis to group participants by their responses to closed-ended and open-ended survey responses, based on methods described by many educational researchers. Cluster analysis is commonly used to group survey participants by identifying their answers to closed-ended responses and coding for themes in open-ended responses. The features and participants are then organized into a dissimilarity matrix with participants as rows and columns as features (see Table 5). Each cell of the matrix indicates if the participant had a certain answer for a closed ended question or theme present in an open-ended question.

Table 5
Dissimilarity matrix, with rows representing n participants P_1,....,Pn and columns for r Motivations, M_1, ..., Mr,

Participants	Motivations				
	M_1	M_2	M_3	…	M_n
P_1	1	0	1	…	0
P_2	…	…	…	…	…
…	7	0	4	…	0
…	0	0	1	…	1
…	…	…	…	…	…
P_n	0	0	8	…	1

Since the goal of cluster analysis is to determine how similar individuals are, the dissimilarity matrix is used to determine some sort of distance index between participants. Different methods of cluster analysis use different ways to determine the distance between participants (Battaglia et al., 2016). A higher measure of distance indicates more dissimilarity between participants. The metrics used for distance are then placed into a new matrix that can be used to create groups or clusters based on the cluster analysis method used (Battaglia et al., 2016). My sources of data for the cluster analysis for motivation are the answers to a question on the enrollment survey and themes that arise from analyzing the introductory forums. The second cluster analysis determined clusters for engagement using click-data. Details for the methodology and results of the cluster analysis process will be shared in Chapter 5.

Phase 2: TSDI and TSIR Participants' Professional Growth

To gain a deeper understanding of how participating in TSDI and TSIR had an impact on professional growth, a follow up survey was sent to study participants. The survey was created based on aspects of the IMPG model. During phase 2 of the study, to assess teachers' growth in their personal domain, guidelines from TSDI and TSIR were used to measure if participants have applied what they learned from the course(s) to their professional practice. Those will be shared below.

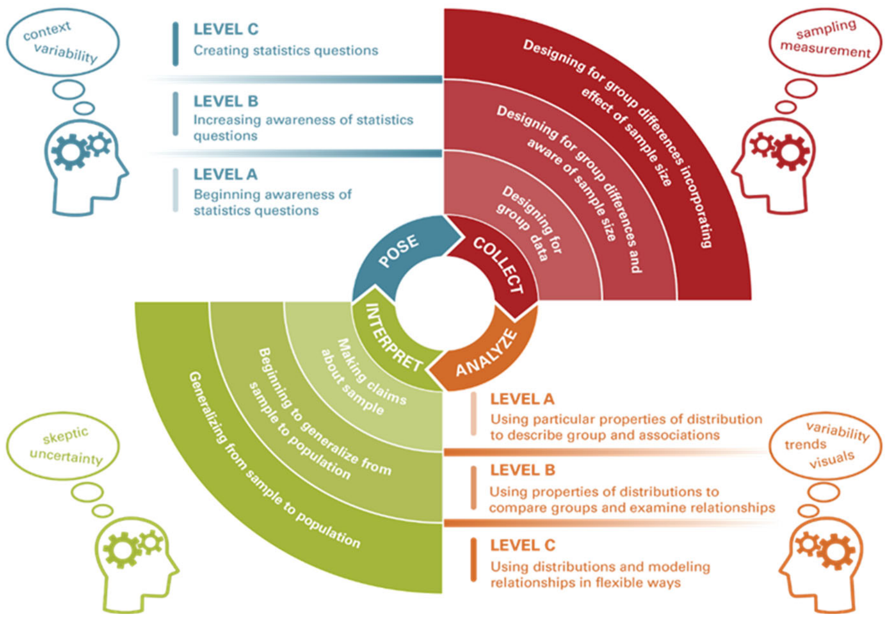
Framework for Supporting Students' Approaches to Statistical Investigations (SASI)

Lee and Tran (2015) created the *Framework for Supporting Students' Approaches to Statistical Investigations (SASI)* (see Figure 8) based on the GAISE framework. This framework was used to guide the analysis of the survey for those that participated in TSDI. The SASI framework is presented to participants of TSDI in Unit 3. Though the participants surveyed may have only engaged in Unit 1 and may not have seen the entire SASI framework, I feel that it is a strong tool to assess what participants may have found as a useful resource in the course. This belief comes from the research on TSDI that has shown that participants believe the SASI framework was one of the most useful parts of the course (Akoğlu, 2018; Hollebrands & Lee, 2020; Lee et al., 2017; Lee et al., 2018; Tran & Lee, 2016).

The SASI framework is used to visualize the three levels of increasing statistical sophistication (level A, B, and C) within each phase of the statistics investigation cycle (pose, collect, analyze, and interpret), as well as incorporating key statistical habits of mind that may occur in each phase (see Figure 6). The four phases of the cycle were introduced in Unit 1 and habits of mind were introduced in Unit 2. Participants of the TSDI course are encouraged to consider the aspects of the SASI framework when planning and teaching their own statistics classes.

Figure 6

Framework for Supporting Students' Approaches to Statistical Investigations (SASI), (Lee & Tran, 2015)



Inferential Reasoning Task (IRT) Guidelines

The *Inferential Reasoning Tasks (IRT) Guidelines* were chosen as an analytical tool for those that participated in TSIR because it appears early in the materials (Unit 1). Though research has not been done to support whether this is an influential document for participants, I believe that the guidelines presented in it are comprehensive of what is presented throughout TSIR. It should serve as a useful framework for determining whether the key concepts of the course are being carried out by participants in their professional life.

One of the first resources encountered by participants of TSIR is a brief paper titled *Using Tasks and Posing Questions to Promote Inferential Reasoning* (Lee, 2017). In this paper

Lee describes inferential habits, general characteristics of good inferential tasks, and categories of questions that can be posed to provide opportunities for students to make inferences. Key inferential habits include using and considering *contextual data*, analyzing data with *multiple representations and statistical measures*, *considering variability, infer a characteristic or trend* beyond the data at hand, and communicates a *level of uncertainty* (Lee, 2017, p.1). Lee provides a list of characteristics and questions that should be considered when creating or choosing inferential tasks. The characteristics of an inference tasks and categories of investigative questions to pose will be referred to as *Inferential Reasoning Task (IRT)* guidelines. These are presented below.

General characteristics of an inference task (Lee, 2017):

- **Context** – choose contexts that are appealing and approachable for students. When possible have students collect their own data or when the data is already collected, be sure students have an opportunity to consider all characteristics of the data and experiment design.

- **Purpose** – ensure that there is a meaningful purpose or reason for the task to make an inference.

- **Collect data with multiple variables** – using data with multiple variables (both quantitative and categorical) allows students to explore trends and relationships as well as determining the affects subgroups may have on those trends.

- **Repeated sampling** – whenever possible provide opportunities for repeated sampling so that the variability among samples can be experienced and accounted for when making inferences beyond a sample.

Categories of investigative questions to pose (Lee, 2017):

- **Comparing Groups** – trying to identify the similarities or differences between groups is a natural inquiry for most people. Asking questions that require students to compare groups are a good way to introduce students to inference.

- **Samples to Populations –** when trying to make a claim about a larger population based on a sample, students must be able to consider sampling techniques. It is also important in these questions for students to consider sampling variability and how statistical measures vary from sample to sample.

- **Competing Models** – these types of questions could include asking which type of distribution a data has or what type of probability model may have generated the data. These questions ask students to consider the best way to describe data.

To answer my second research question (*How did participation in statistics education online professional development impact ongoing professional growth for participants?),* I gathered quantitative and qualitative data to describe the ways that participating in the courses intended for statistics educators influenced professional growth. The source of data is the follow-up survey sent to all participants.

Follow up survey

The follow-up survey was used to provide a general description of the changes in the personal domain, domain of practice, and domain of consequence. Since professional growth might not be evident at the end of a professional development experience (Kennedy, 2016), it will be important to look at this data collected after participating in the courses. There are also participants who engaged in TSDI and then TSIR. Those individuals will also provide a unique experience of seeing if they changed at the end of each course.

Data will be gathered once participants have had a significant amount of time (at least 1 year) to reflect and enact after the experience, since the last offering of TSDI was in Fall 2018 and the last offering of TSIR was in Spring 2019. The survey (see Appendix C) includes questions about how the course(s) impacted their knowledge, beliefs, and skills (personal domain), statistics teaching practice (domain of practice) and any salient outcomes or changes to their professional life after participating in the course(s) (domain of consequence). Appendix C provides detail of how each question in the survey maps to model for motivation, engagement, and professional growth.

The survey asks questions specific to the domain of consequence. To describe change in this domain, I grouped questions in the survey by salient outcomes, student outcomes, and community influence. I believe that describing changes in the domain of consequence is harder than describing changes in the domain of practice. For this reason, I provided a small vignette of what these outcomes may look like for a participant before each group of questions. I hoped that this will help participants to describe their own view of change in this domain.

The same survey was issued for all participants of TSDI and/or TSIR. Closed- and open-ended questions asked about changes in practices specific to data investigations (TSDI) and inferential reasoning tasks (TSIR). Participants only completed the sections specific to the course(s) in which they participated. I used the SASI framework and IRT guidelines in the development of these questions as well as in the analysis of the questions. Quantitative analysis of closed-ended questions and qualitative analysis of open-ended questions provide an overall description of changes in the personal domain, domain of practice and domain of consequence.

The survey was sent out in March 2021 to all 1,592 participants. Unfortunately, only 50 participants completed the survey. This low response rate was expected. Teachers were faced with unprecedented hardships and stress placed on them during the 2021-2022 school year because of adjusting their teaching strategies due to the COVID19 worldwide pandemic. Almost all instructors at all levels of teaching had to teach fully online or in a hybrid format for almost the entire year. Voluntary participation in a survey on top of the other responsibilities they had to juggle was likely not a high priority. Chapter 6 presents a summary of the results of the survey from this small sample of participants. Though this sample is not representative of all the participants, they still gave very good feedback on the effects that their participation in the courses had on their professional growth.

Ethical Considerations

This research is a follow up-study to another study that has been approved by the Institutional Review Board (IRB) of North Carolina State University. Phase 1 of the study falls under an approved IRB (4107) by North Carolina State University, and the secondary data request was made to the data gatekeeper following approved IRB procedures. For this prior IRB, participants consented for data to be collected by agreeing to the MOOC-Eds terms and conditions during the registration process. Participants had the option to unenroll from the course at any time. Data collected included embedded surveys (including the registration survey), discussion forums, and click-log data. Each participant was assigned a unique identifier and all data was blinded and stored on a password-protected secured server. All data needed to complete Phase 1 of this study is stored electronically, and password protected on Friday Institute servers.

Phase 2 of the study required that participants be contacted via email (see Appendix C) to complete a survey and opt into a future study by submitting tasks and participating in an interview. The prior IRB included that contact information would be retained and participants may be contacted in the future for further study. A new IRB (22423) was approved to gain permission to ask participants to participate in a survey, submit sample tasks, and participate in structured interviews. I submitted an interview protocol (Appendix F) and task submission guideline for this IRB that I hope to use in a future study. Though approved, due to the ongoing pandemic in 2020-21, those pieces of data were not collected for this current study.

To protect participants' identities, all data is stored on a password-protected online drive. The unique identifiers assigned to participants for Phase 1 will be used in analysis. Unique identifiers may be assigned pseudonyms to make reporting easier.

CHAPTER 4 USING TOPIC MODELING TO IDENTIFY PARTICIPANT MOTIVATIONS FOR ENROLLING IN ONLINE PROFESSIONAL DEVELOPMENT FOR STATISTICS EDUCATORS

Journal

This chapter presents a journal ready manuscript to be submitted to the *Journal of Learning Analytics.* The *Journal of Learning Analytics* (JLA) is the first journal dedicated to research focusing on the challenges of collecting, analyzing, and reporting data that is specific to the field of learning. The journal hopes to connect researchers, developers and practitioners who are interested in better understanding learning through new techniques and tools in the field. Topics include educational perspectives, computational perspectives, information and sense-making perspectives, and institutional and societal perspectives. This manuscript will be submitted as a research report that describes original empirical research. Research papers should be no longer than 8,000 words in length, excluding tables, references, abstract, key words, and acknowledgements. Each research paper should also include a *Notes for Practice*. These notes should be bullet points outlining an overview of the established knowledge on the topic, a summary of the contribution of the paper, and key implications of the paper's findings for practice, policy, and implementation of research.

Abstract

Computational text mining, such as topic modeling, is a field of learning analytics that has proven effective in analyzing large volumes of text to identify common themes. In traditional qualitative approaches of analyzing text, researchers take turns reading texts, developing themes (or codes) and applying codes to the text to identify common themes. Combining these two approaches to advance the fields of text mining and qualitative analysis may prove useful in analyzing large datasets such as discussion posts in massive open online courses. In this study, qualitative coding of discussion forums was combined with topic modeling to identify participants' motivation for enrolling in two successive statistics education professional development online courses. Three topic modeling approaches were used, utilizing an unsupervised modeling technique and a semi-supervised modeling technique. The three topic modeling approaches were compared to determine which participants were assigned motivation themes that most closely aligned to their posts made in an introductory discussion forum. A discussion of how each of these techniques can be useful for identifying themes within discussion forum is included.

Notes for Practice

- This paper explores how topic modeling can be used to identify motivations of participants enrolling in online professional developing using their discussion forum posts, a total of 1,099 posts.
- Three topic modeling methods are shared that could be reproducible for other researchers interested in using this sort of analysis method.
- It was found that methods with fewer identified themes tended to have a higher validity rate.

Keywords

topic modeling, MOOCs, online professional development, discussion forums, motivation

Introduction

Massive Open Online Courses are a form of online professional development (OPD) that can be a convenient way to create a community of learners, as well as provide professional development (PD) that is on demand and timely. The rising enrollment in Massive Open Online Courses (MOOCs) has led many researchers to explore participant motivation for enrolling in a course, as well as patterns of engaging in course materials (Frankowsky, et al., 2015; Perna, et al., 2014; Thompson, et al., 2016; Wilkowski, et al., 2014). For curriculum developers and course instructors, "the goal for curriculum development has typically been to create a linear sequence of content in an optimal order of increasingly complex content. As computer-based (eLearning) instructional environments became more prevalent, there arose more interest in the flexibility and the usability of instructional content and its delivery mechanisms" (Wiebe & Sharek, 2016, p.55). This new typ e of course design attracts a diverse group of learners with varying goals to MOOCs.

Identifying motivation for enrolling in a MOOC is often achieved by asking questions on enrollment surveys (Creager, et al., 2018; Hollebrands & Lee, 2020; Moore & Wang, 2020; Wilkowski, et al., 2014). Using enrollment surveys limits the motivations that will be identified to just those that are specified on the enrollment survey. A richer source of data that can be used to identify motivation lies in reading introductory discussion forums that participants respond to where they are asked to answer questions such as *why are you taking this course?* Topic modeling is an unsupervised learning method that can be used for classification of large groups of texts, such as discussion forum posts, into discrete groups of words (Silge & Robinson, 2019). Since reading and identifying themes for motivation on so many posts can be a daunting task, using topic modeling may be an appropriate alternative to traditional qualitative methods of identifying themes. This has led to the research question, *In what ways can topic modeling be an effective tool to identify motivation of participants who enroll in online professional development courses for statistics educators?*

Literature Review

Since MOOCs provide participants autonomy to engage with elements of the course to reach their goals, it is important for researchers to determine what motivates participants to enroll in a course. Self-determination theory can help in understanding motivation by exploring the conditions that motivate humans to initially engage in challenging tasks (Wiebe & Sharek, 2016). According to self-determination theory, motivation can come from intrinsic or extrinsic influences and factors. Intrinsic motivation is when an individual may pursue a task for the sheer human pursuit of learning or creativity. On the other hand, extrinsic motivation comes from outside influences or awards that require the completion of a task (Eccles & Wigfield, 2002; Wiebe & Sharek, 2016). Extrinsic motivation can also arise from being part of a social group (Moore & Wang, 2020; Wiebe & Sharek, 2016). Since MOOCs attract a diverse range of learners with many different goals, motivations will vary across all participants (Deboer, et al., 2014).

Hollebrands and Lee (2020) analyzed participants in three online professional development courses for mathematics and statistics teachers (middle grades through introductory college level) offered between September 2015 and May 2019 (14 total offerings). They found that in the enrollment survey, of those that responded to a question asking about their reason for enrolling in the course, 44.8% selected the option that they enrolled "to deepen their understanding of course content" and 35.1% indicated they enrolled in the course "to collect resources and tools to use in their own practice". Other motivating factors for enrollment in these types of MOOCs for mathematics and statistics educators have not yet been fully explored.

Qualitative Approaches to Analyzing Discussion Forum Data

Discussion forums in MOOCs are often the only spaces where participants can interact and express their individuality in an online environment. Asynchronous discussion forums (those that participants can post to throughout a given length of time and not at a set time) give participants the opportunity to provide rich discussion. In these forums, participants have time to think about their contribution to the discussion for a longer time than in a face-to-face conversation (Gao, Wang, & Sun, 2009). Many studies have analyzed participation in online discussion forums by analyzing frequency of posting in forums (Gao et al, 2013; Garrison et al., 2001; Hara et al., 2000; Kop et al., 2011). Further qualitative analysis of what people are discussing in forums provides an even richer description of interactions, with a growing number of researchers trying to determine the best way to analyze the data (Ezen-Can, et al., 2015).

Though the number of posts in discussion forums can be large, researchers have tackled analyzing the data using traditional qualitative methods of reading large amounts of posts to identify themes. The following are examples of this technique. Nandi et al. (2012) used a grounded theory approach through open coding, to identify the quality of interactions between participants and instructors in two open online courses that had 1,352 participants. Wang et al. (2015) used a discourse framework in an analysis of discussion forum posts for a Psychology MOOC to hand code 7,990 posts. Lee et al. (2020) used open coding (on 977 posts) to identify what triggers may have caused a shift in participants' beliefs or perspectives during their participation in an online professional development course for statistics teachers.

Topic Modeling Approaches to Analyzing Discussion Forum Data

The studies mentioned in the previous section showcase the range of questions that can be answered by using qualitative data analysis approaches, but these approaches can take a lot of time and a lot of training to achieve consistency between coders. Text mining is a *computational* approach to analyzing large collections of text to try to make meaning of the data (Hearst, 2003). Topic modeling is a type of text mining that has been used to identify themes of discussions in discussion forums. Topic modeling is a method that can be used for classification of large groups of texts into discrete groups of words (Silge & Robinson, 2019). This section will explore efforts to analyze discussion forum data in MOOCs using topic modeling.

Unsupervised topic modeling uses different modeling approaches to group words, based on certain statistical criteria, that become the topics for a large corpus of data (Silge & Robinson, 2019). It is up to the researcher to interpret these topics as they apply to the data. Ezen-can et al. (2015) used an unsupervised modeling technique to create seven clusters from 550 discussion posts that were part of a MOOC for educators on digital learning. Latent Dirichlet Allocation (LDA), an automatic topic modeling technique, was then used on the posts in each cluster to identify the textual themes. Reich et al. (2016) used topic modeling to analyze themes in two forums (one with 195 posts and one with 155 posts) in an educational policy MOOC. They used the topics found to describe patterns of discussion in the forms on the use of school vouchers and feelings about instituting the Common Core. Vytasek et al. (2017) applied four unsupervised topic modeling approaches to a set of 813 posts in a Medical Statistics MOOC. They found that the best way to make sense of the topics was to nest the topics as subtopics that are part of more general topics.

Seeded topic modeling is a semi-supervised learning method that identifies topics using a predetermined seeded dictionary of terms (Watanabe & Xuan-Hieu, 2020). Ramesh, et al. (2014) used a semi-supervised learning method of fitting a LDA model by inputting a seeded dictionary of terms created as a source to identify topics that they assumed should be common to the context of MOOC discussion forums. Wong et al., (2019) were able to show that using a seeded LDA method was effective for tracing forum posts back to topics specific to a MOOC. This study will use the background of the unsupervised and semi-supervised modeling techniques that were used in these studies.

Nelson et al. (2021) recognized the gap that may exist between hand coding text and using computational methods to identify themes in socially constructed content. They used three common computer text mining approaches, dictionary, supervised, and unsupervised machine learning, to compare the results of the computerized text mining to previously hand coded textual data. Newspaper articles had already been coded based on themes on income inequality. Nelson et al. (2021) found that the unsupervised machine learning method worked best and had a 0.91 alignment rate to the hand coded articles, meaning 91% of the articles were coded with the same theme as the hand coding method.

Statistics Education Online Professional Development

The data in this study is a large collection of posts from discussion forums in two online professional development courses designed for statistics educators, primarily those teaching in middle schools (age 11) through introductory college courses. This section will give an overview of the need for and importance of these courses. The context of this study is critical in understanding the outcomes of the topic modeling approaches used.

Statistics has made an impact in the mathematics curriculum, which has led to challenges in preparing teachers to teach statistics. Professional development opportunities for teachers of statistics have been implemented to foster the knowledge, skills, and dispositions necessary to effectively teach the subject. The American Statistical Association (ASA) endorsed the *Statistical Education of Teachers* (SET) report to guide pre-service and in-service teacher preparation for teaching statistics (Franklin, et al., 2015). The SET report states that statistics teacher educators should support statistics teachers at all levels by helping K-12 teachers have knowledge and skills of teaching statistics beyond what was required for their initial certification, encourage teachers to strive for continual improvement in their teaching, and join with teachers to learn at all different levels (Franklin, et al., 2015).

The SET report stresses the need for professional development at the local or state level to aid mathematics teachers to teach statistics, while also recognizing the limitations of providing such professional development (Franklin, et al, 2015). Online professional development (OPD) can be a way to provide this PD for those who need it (Lee & Stangl, 2015). Dr. Hollylynne Lee and her team at the Friday Institute for Educational Innovation have created two online professional development courses for statistics educators titled *Teaching Statistics through Data Investigations (TSDI)* and *Teaching Statistics through Inferential Reasoning (TSIR).* Each course is meant to enhance teachers' understanding of statistics and teaching strategies in middle school classes through introductory level college courses.

Methods

Context and Participants

The two online courses that are the focus of this study (TSDI and TSIR) were created to provide high quality online professional development for statistics educators. The "overarching goal of [TSDI] is to engage participants in thinking about statistics teaching and learning in ways that are likely different from their current practices in middle school through college-level introductory statistics" (Lee, et al, 2020, p. 4). TSIR was also intended to attract educators in middle grades to college, interested in strengthening their statistics pedagogy. This course was meant to be an extension of the materials in TSDI while emphasizing inferential reasoning.

TSDI was taught seven times through The PLACE at the Friday Institute for Educational Innovation, with the first offering in the Fall of 2015 and the last in the Fall of 2018. A total of 3,115 people enrolled in TSDI. TSIR was offered three times, in Fall 2017, Spring 2018 and Spring 2019. A total of 700 people enrolled in TSIR. The courses were asynchronous, meaning that participants were able to complete course work at their convenience; they were not required to log in to the course at a predetermined time.

Of the 3,815 total people that enrolled in either course, 1,592 accessed at least Unit 1 of a course, and those are the participants included in this study. Other researchers have found a high drop off rate of participants after the first unit of MOOCs (Erikkson, et al., 2017; Onah, et al., 2014). Hollebrands and Lee (2020) found this high drop off rate occurred between the Orientation Unit and Unit 1 of the courses in this study (as well as one other MOOC-Ed offered through the Friday Institute), which likely indicates that participants visited and found they were no longer interested in the course or no longer had the time to participate. For these reasons, only those who participated in at least Unit 1 (1,592 participants) are included in this study.

There are participants who enrolled in more than one course. These may be individuals that initially engaged in a course and did not complete it, and later enrolled in another offering. Or they are individuals who enrolled in either TSDI or TSIR, then decided to take the other course. Since motivation can change over time, it was decided to treat each time a person took a course as a separate participant. Thus, participants are identified using their numeric user identification number *and* course identification number (userid_bycourse). Of the 1,592 unique participants, 357 registered for more than one course, resulting in 1,949 participants for analysis purposes (i.e., an individual is considered a different participant for each time they enrolled in a course).

There are instances when an individual may have enrolled in a course and not participated in Unit 1 of that course but enrolled in another course offering and did participate in Unit 1. All instances of an individual's participation were kept for analysis (if they engaged in Unit 1 of at least one course), since these participants are part of a larger project analyzing engagement and motivation. For the remainder of this paper, the term participant refers to a participant who is enrolled in a specific course and accessed at least Unit 1 of at least one of the 10 course offerings in this study.

Discussion Forum Data

The data for this study is from the first discussion forum, which is found in the Orientation unit in each course. This unit provides participants with a description of the course, advice on how to interact with different components of the course, an introduction to the instructor, and the first discussion forum titled *Meet Your Colleagues*. In TSDI, there is also an opportunity for participants to take an assessment to evaluate their confidence level for teaching statistics. TSIR provides brief highlights of materials taught in TSDI in the Orientation unit. The *Meet Your Colleagues* prompt states "Introduce Yourself! In the title of your post, include your name and location and in the body, we hope you'll take the time to share a bit about yourself, including why you are interested in this course". Participants can either create a new thread or respond to other participants. Participants will often post their own response to the forum prompt in another participant's thread. Because of this, initial posts and replies will be included in the corpus of data for this study. After the Orientation unit, each course has 5 units of learning materials.

Discussion Forum Data Preparation

This study is specifically designed to identify themes for discussions around motivation, instead of a general exploratory topic modeling approach. In unsupervised topic modeling there are often topics that are found that do not always make sense to the user (Hu et al., 2014). To avoid the general topics that naturally arise, this data was prepared prior to modeling so that the discussion, or *noise*, that is not centered on motivation was reduced as much as possible. In the topic modeling analysis section, an exploratory topic modeling approach will be shared that will further support the need for this data preparation.

Identifying parts of posts that may prove useful for identifying themes for motivation for taking these specific courses may not be obvious to anyone able to perform topic modeling. Thus, it is of critical importance that the researcher is familiar with these courses and the participants. The authors' expertise is in statistics education research, specifically online professional development for statistics teachers, so they are familiar with what motivates people to enroll in courses like these. Additionally, the authors have worked with discussion forum data from these course offerings in the past, offering a unique perspective to the best ways to prepare this specific set of data for topic modeling.

All posts from the *Meet your Colleagues* forum in the Orientation Unit were collected from each of the course offerings. Posts were filtered to only include the participants of this study. This resulted in 1,639 posts. (Note: Not all participants in this study posted in this forum.) These posts were first blinded by removing all mentions of names or locations. Pseudonyms were not used to replace these names; they were simply left blank. All the posts were then read to isolate only entries that were related specifically to motivation. Many entries included introductory information about the participant, such as what they teach, where they are from, etc. For instance, in the following post, the first part is introductory information about where they teach. Only the second sentence was retained for analysis.

Hi, all. I have taught an Elementary Statistics course at - Community College for 14 years. ;I have a few classroom activities that I use regularly, and I would like to get additional ideas for activities to keep my students engaged.

There are also entries responding to other participant posts that do not address motivation at all. For example, *Hi ! Thank you so much for your kind words :) I can't wait to start!* and *Hi ,What are the chances that we would end up in a MOOC together?!* These posts were completely removed from the dataset, as well as similar ones that did not seem related to motivation. This resulted in 1,099 posts for topic modeling.

This set of 1,099 posts includes multiple posts that may have been made by the same participant. The posts could have been initial posts creating a new discussion thread or replies to other participants' posts. Replies were kept for analysis purposes as well as initial posts since there were often clues to their motivation for taking the course within reply threads. Since we are interested in what motivates each participant to take the course, any posts that were made by the same participant in a specific course were merged so that when performing topic modeling the corpus of posts from each user would be read as one document, rather than multiple documents from each user. This eliminated the possibility that more than one topic could be applied to any participant. In all, there were 946 unique participants posting in the discussion forums. Thus, there were 946 documents that were analyzed for topic modeling. These documents are the unit of analysis. The following section describes how the documents were broken down into strings of text for the topic modeling analysis.

Identifying Text Terms in Documents

To perform topic modeling, posts must be broken down, or tokenized, into strings of individual words (Silge & Robinson, 2019). These individual words form what are called a *document term matrix*, or DTM. In the DTM, each row represents one participant's document, and each column represents one word. The count of each word is recorded for each participant in the corresponding cells. The DTM was created in R using the CreateDTM function which is part of the *textmineR* package (v.3.0.4; Joanes & Doane, 2019).

There are some words that will appear more frequently than others and skew the results of topic modeling. *Stop words* are commonly removed from a DTM prior to performing topic modeling to ensure that common English words such as *a, the, and,* etc. do not become grouped into topics (Silge & Robinson, 2019). The DTM was anti-joined with a stop word dictionary to filter out these terms.

In addition to removing stop words, it is common in topic modeling to group words together that have the same stem (Silge & Robinson, 2019). For instance, *learn*, *learning*, and *learned* all have the same connotation. The Porter stemmer method (Porter, 1980) was used to stem the words in the posts using the stemmer function in the *SnowballC* package (v.0.7.0;Bouchet-Valat, 2020). The decision to use stemming was made after an exploratory topic modeling approach was done without stemming words. This exploratory approach had words such as *statistics, statistical, statistic* or *learned, learning, learn* appear so often in the topics that other words that may be helpful in identifying topics did not appear as top words. After the stemming approach was used, which combined *statistic, statistical, statistics* to just the stem *statist.* This made room for other meaningful words to appear such as *ap* or *science*. Since we know many AP Statistics instructors enrolled in these courses, it made sense that the desire to improve an AP course may be a driving motivation to enroll.

The DTM can be made using one word grouping or any n-sized groups of words. For this analysis, the DTM was made of one- and two-word groups, unigrams and bigrams, respectively. Successive two-word groups were used to capture terms such as *build confidence* or *statistical thinking*. We hoped including these terms would help to distinguish between words such as *learn_statistics* and *teach_statistics.* If we did not use bigrams statistics would just be counted once, but we know that the motivation to learn statistics is much different than being motivated to teach statistics. Any two successive terms were considered bigrams. For instance, the phrase *enjoy teaching statistics,* would be considered 5 words, the three individual unigrams (*enjoy, teaching,* and *statistics)* as well as the two bigrams, *enjoy teaching* and *teaching statistics.* It is possible to look at n-gram groupings higher than n = 2 to capture more phrases. Text mining researchers have found interpreting topics with these higher order phrases is possible, but often requires programming methods specific to phrases, instead of words, which were not used in this study (Das et al., 2016; Huang, 2018; Schmiedel et al., 2019).

After the DTM was created, topic modeling was performed on a random set of 100 posts to see if any words outside of common stop words appeared more often that may not have meaning when identifying motivation. This topic model had the following terms appear most often; *ways, wait, looking forward, hope* and *take*. These words were often used by participants to introduce what they wanted to accomplish. Phrases such as *looking forward to learning with you*, *hoping to learn how to,* or *I can't wait to,* appeared so often that the topics seemed meaningless. These terms were removed from posts before creating the DTM.

The following illustrates how the steps identified above were used to clean the posts that were used to create the DTM. Below are the combined posts for participant 4451_9.

> *My Name is xxx, I teach at xxx in xxx. I teach AP Statistics and am hoping to get some ideas of how I can encourage my colleagues to incorporate more statistics and data collection into their courses so that a course such as mine isn't the first time that students are exposed to Stats. It seems that most of high school courses lead students to Calculus, but I think that Statistics is much more interesting and applicable to more students.*

After going through the steps described above, the following words were included in the DTM for participant 4451_9. Cleaned documents, like the one below, were used to create the DTM. Stop words and stemming still appear in this step, those were not filtered out until the creation of the DTM.

> *I teach AP Statistics and am   get some ideas of how I can encourage my colleagues to incorporate more statistics and data collection into their courses so that a course such as mine isn't the first time that students are exposed to Stats.*

There were often times participants introduced which classes they were teaching that were not in the context of motivation. The original post above mentions what classes the participant is teaching, but this seems relevant to their desire to expose students to statistics in courses other than AP Statistics. Other times, participants would specifically say they are taking the MOOC to prepare for new changes in the curriculum in their classes or are preparing to teach AP statistics for the first time. The inclusion of phrases was up to the discretion of the authors.

After removing stop words and performing the porter stemming functions on this corpus of 946 documents, the resulting DTM was a matrix with 946 rows (representing the participants) and 8,933 columns (representing the 1- or 2-word groups). The cells of the matrix are the number of times each word(s) occurred for that participant. Figure 7 shows an excerpt of the row of participant 4451_9.

Figure 7

Example of the non-zero entries of a row of the DTM for participant 4451_9

	teach	statist	teach_ap	idea	encourag	encourag_colleagu	incorpor_statist	incorpor	data	data_collect	stat
4451_9	1	2	1	1	1	1	1	1	1	1	1

Note the complete row for each participant has all possible 1- and 2-word groupings of all documents, 8,933 columns. Figure 7 shows a subset of *some* of the nonzero columns. The phrase *incorporate more statistics* becomes *incorpor_statist* after the stop word *more* was removed and the terms were stemmed to the root of the words. Note that the count is recorded for *incorpor, incorpor_statist,* and *statist*. There were several times participants wrote the word statistics or stats, these were considered different using this stemming method. Also note that the order of the words matters when the DTM is created. For instance, *incorpor_statist* is counted as 1, but *statist_incorpor* has a value of 0.

Topic Modeling Analysis

A qualitative analysis approach to identify the themes for motivation of the participants to take these courses would include researchers reading the posts and identifying themes using qualitative coding techniques (Creswell, 2013). The purpose of this study is to determine the ways in which topic modeling could be an effective tool to identify themes without traditional qualitative coding. There were three topic modeling approaches used in this study, referred to as Method 1, Method 2, and Method 3. This section begins with an overview of an initial exploratory topic modeling approach, followed by the procedures, results and validation approaches for Methods 1, 2 and 3.

Exploratory Topic Modeling

To determine if topic modeling would be appropriate for identifying themes for motivation of participants, an exploratory topic modeling approach was used. This initial approach to topic modeling proved to be useful to determine how the data should be prepared to create the DTM for the other methods.

The exploratory topic model and Method 1 used an unsupervised learning method, using a computer algorithm to determine a list of unknown topics without input from the researcher. Though the number of topics must be predetermined, which topics are chosen is entirely determined by the topic modeling algorithm. A DTM was created to fit a Latent Dirichlet Allocation (LDA) model, a popular method for fitting a topic model (Silge & Robinson, 2019). LDA considers every document as a mixture of topics and every topic a mixture of words (Silge & Robinson, 2019). This means that for any document the LDA model may deduce that the terms in document A are 60% from topic 1 and 40% from topic 2, not assigning each document only 1 topic. Each topic is made up of a mixture of words, which can also overlap. Topic 1 may have the words “bell”, “ring”, and “chime” and Topic 2 could have “married”, “ring”, and “partner”. LDA is a mathematical model that determines the likelihood of a document relating to each topic while simultaneously determining the likelihood that a word belongs to a topic (Silge & Robinson, 2019).

The DTM used for the exploratory topic model was not the one described in the previous data preparation section. This DTM was the original collection of 1,639 posts of the participants in the introductory discussion forum, with each row representing a post, each column the possible words and each cell the count of each word occurrence. This DTM did use the stop word method that was utilized for the other methods as well as allowing 1- and 2-word groupings but did not include any stemming method.

The exploratory topic model yielded topics that were not able to be interpreted as themes for motivation. But these results were useful in identifying issues that needed to be addressed in the preparation of the data to create applicable topics. Since these topics were meant to identify themes specific to motivation, there was a lot of *noise* created from the introductory discussion that naturally happens in this sort of forum. This led to the filtering of the data to only include discussion specific to reasons for why participants enrolled in the course. The exploratory topic modeling also led to the inclusion of the stemming method because there were topics that included words that were just iterations of the word statistics or iterations of the word teach or learn, for example. This made the topics meaningless in this specific context.

Finally, the exploratory topic model led to a larger issue, which was identifying an appropriate unit of analysis. This exploratory approach was identifying a topic for each *post*, making individual posts the unit of analysis. A larger research study that includes these participants seeks to identify the motivation of each participant, so it was important to isolate one topic for each participant. It was with this exploratory approach that the importance of creating a document that represented a participant's collection of posts was more important than identifying the topics of each post. For the remaining methods, a document including all posts by a participant in a course is the unit of analysis. All these decisions led to the data preparation described previously that was used for Methods 1, 2, and 3.

Validation of Topics for Each Method

To validate how each of the following methods performed on appropriately assigning topics, a method like interrater reliability (IRR) was used. In qualitative research, "IRR is a statistical measure of agreement between two or more coders of data" (McDonald, et al.,2018, p. 2). Coders read qualitative data using a set of agreed upon codes, then determine how closely their interpretations match. For the methods described here the two coders are the software packages and the primary researcher, and the codes are the topics identified in each method. Like IRR, for topic modeling Boussalis and Cohan (2016) suggest that researchers use a process called *concurrent validation* to manually code a sample of data and compare those results to the results of a topic model to test the model's validity. This suggestion is used with the 3 topic modeling methods of this study, but instead of checking the validity of a sample, the validity of the entire data set is checked.

A spreadsheet that contained the 946 documents that were used for all 3 methods was created. Recall, the documents used were the combined and edited posts of all 946 participants that were identified as having shared some sort of motivation for enrolling in the course in the orientation discussion forum. A column for each method was created, with the identified topics for Method 1, 2 and 3. Each document was then read in its entirety and assigned a validity of Yes (Y) or No (N) to whether the researcher agreed with the topic assigned by each method. The validation results for each method will be shared in the following sections.

Method 1

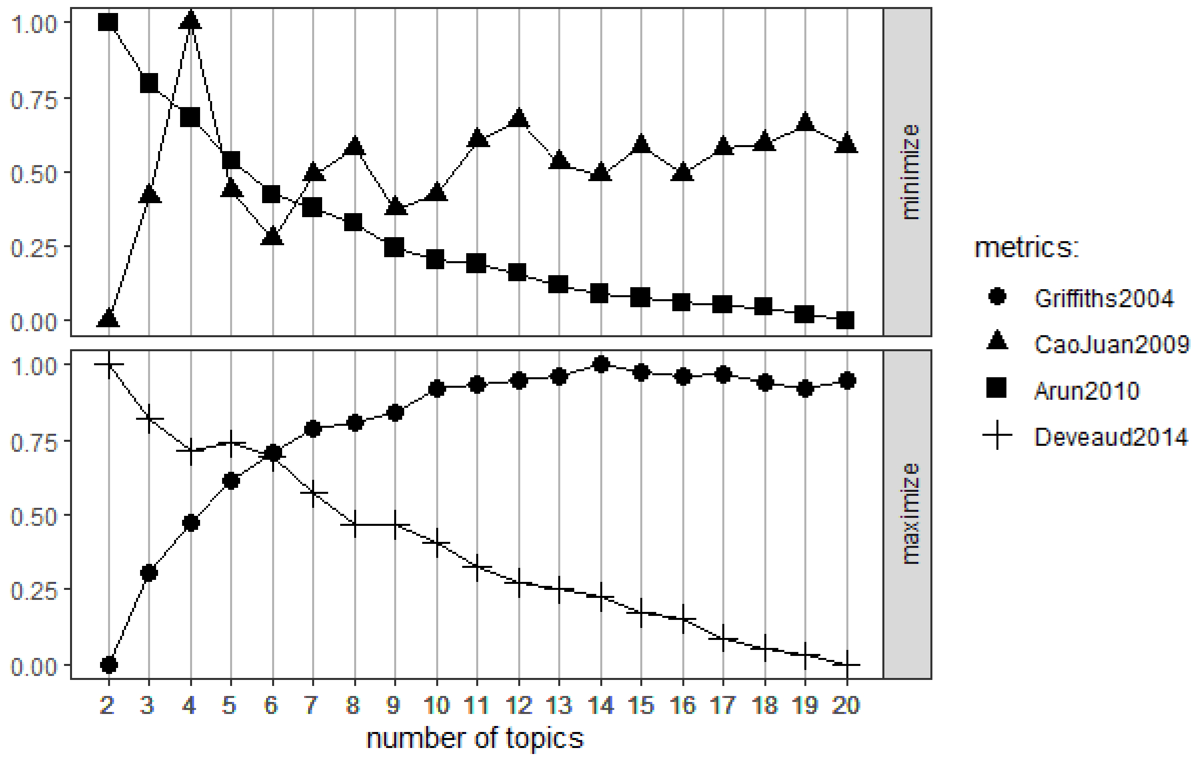
Method 1 procedures were the same as for the exploratory topic modeling approach, except the DTM was the one described in the data preparation section above (see Appendix H – R Code for Topic Modeling Method 1, Unsupervised Learning Method for R code). The LDA function in the *topicmodels* package available for R (v.02-12; Grün et al., 2021) was used to assign topics to the DTM created for the discussion posts related to motivation. The LDA function uses probabilistic functions to determine a beta value and gamma value using a predetermined number of topics. The beta value is the probability that a single word belongs to a topic. The gamma value is an estimated proportion of words from each document that belong to a topic (Hornik & Grün, 2011).

Determining the number of topics

Many researchers have created metrics that can be minimized or maximized to determine the ideal number of topics to fit the LDA function (Arun et al., 2010; Cao et al., 2009; Deveaud et al., 2014; Griffiths & Steyvers, 2004). The *ldatuning* package in R uses the metrics created by these four researchers to attempt to fine tune the optimum number of topics for a given set of documents (v1.0.2; Nikita & Chaney, 2020). The *FindTopicsNumber* function from the *ldatuning* package was used to determine the ideal number of topics between 1 and 20. The metrics *Griffiths2004, CaoJuan2009, Arun2010,* and *Deveaud2014* were found for the DTM for this study. Figure 8 shows a graph generated of the metrics for each number of topics.

Figure 8

The ideal number of topics as determined by the four metrics available in the ldatuning package in R.



The ideal number of topics for the Arun2010 and CaoJuan2009 metrics occur at the minimum values. In Figure 8, the minimum for Arun2010 occurs at 20, steadily decreasing from 2. The minimum for CaoJuan2009 occurs at 2 and again a slight dip at 6. For the Griffiths2004 and Deveaud2014 metrics the ideal number occurs at the maximum points. The maximum occurs at 2 for Deveaud2014 with a steady decrease down to 20, with a slight increase at 5. For Arun2010 the metric increases from 2 to 20 with a maximum at 20. It seems that any number of topics between 4 and 6 would be ideal since this is where the metrics are close to one another. For this study, 6 topics were chosen to identify participants' motivation to take the courses.

There is a possibility that there may have been a number of ideal topics past 20 that would have optimized these metrics better. Participants are required to complete an enrollment survey when they register for these courses. In this survey there are 14 broad goals that participants can choose from as their motivation for taking the course, determined by the development team for the courses based on prior research and experiences learned from similar courses (Appendix G). For this reason, it was decided to not look beyond 20 topics for an ideal number, since the development team has already identified these 14. Additionally, 6 topics were chosen over 4 since we also know that participants already have chosen a large range of different motivating factors based on the enrollment survey.

Identifying Topics using Method 1

Method 1 used the LDA function in the *topicmodels* (Grun, et al., 2021) package in R to assign a mixture of words to each topic as well as assigning a topic to each document (Silge & Robinson, 2019). The LDA function requires a DTM and a user assigned number of topics, *k*. For this function, the DTM constructed for the discussion posts was an input as well the number of topics, $k = 6$, based on the results of the *FindNumberTopics* function. An option to set a seed was also an input so that the topic assignment was reproducible.

The LDA function produced six topics. Themes for these topics were identified using the 20 words in each topic with the highest beta value. The beta value is the probability that a term is generated from that topic (Silge & Robinson, 2019). The *bag of words* for each topic were analyzed to identify a motivating theme for each topic. To do this, the six bag of words (20 words for each topic) were collected and distributed to other mathematics and statistics education researchers to ask for their input. Six volunteer researchers read the 20 words associated with each topic and completed the prompt "This group of participants is motivated to take this course because…". The volunteers were comprised of a statistics professor, three mathematics education professors, and a mathematics professor. Using these responses, as well as knowledge of the goals of the course, and reading many of the discussion forums prior to analysis, the researchers decided on themes for each topic. The themes identified will be discussed in the results section.

The LDA function also assigns each document and its assigned topic a gamma value. The gamma value is the proportion of words from each document that are generated from the assigned topic (Silge & Robinson, 2019). The higher the gamma value, the higher the probability that the document aligns to a given topic. The LDA function can assign a document to more than one topic. For instance, a document could have a gamma value of 0.55 for topic 1 and 0.45 for topic 2. This would show that about 55% of the words in the document are generated from topic 1 and 45% from topic 2.

For this study, each document is the collection of posts by a user in a single course. It was decided to only include topic assignments that had a gamma value greater than 0.5 for each participant. This ensures that most of the words that a participant posted in the forum are generated from the assigned topic. There is certainly the likelihood that more than one topic is applicable to a participant. But for the purposes of this research, we were interested in the one topic most likely associated with a participant. The topic for each participant was recorded. Of the 946 documents (collection of posts), all but six had a gamma value greater than 0.5. Thus 940 documents were assigned topics.

Method 1 Topics

Table 6 shows the topics that were generated using Method 1. The LDA function generates a beta value for each term and topic. The results here include the top 20 terms with the highest beta value. The “bag of words” column shows these words. They are listed in order from highest to lowest beta value as defined by the LDA function.

The title and theme of each topic were determined after trying to make sense of the bag of words applied to each topic. The title and themes were created by the researcher and specific to the context of this discussion forum data. Using the knowledge from prior research about the topics in this MOOC, research specifically done on users of these MOOCs, reading the discussion forums in this study, and using the input from the other volunteer researchers who read the bag of words, the titles and themes were finalized by the author before validating whether the topics were applied appropriately or not by the algorithm.

Table 6

Topics for Motivation to Enroll Identified using Method 1

Topic	**Theme for Motivation**	**Description** This group of participants...	**Bag of Words**
1	Teach and understand statistics using data	... is excited and interested in learning to teach and understand statistics with data	Statist, teach_learn, student, teach_statist, excited, interested, class, educate, love, mooc, math, idea, learn_teach, understand, excited_learn, data, knowledge, stat

Table 6 (continued).

Topic	Theme for Motivation	Description This group of participants...	Bag of Words
2	Preparing to teach new curriculum that uses statistics	...is interested in learning and teaching statistics (using technology and data) especially as it pertains to new curriculum, such as math classes in the common core, that use statistics.	statist, teach, learn, student, stat, teach_statist, class, data, teacher, curriculum, common, core, common_core, algebra, technological, math, year, interest, improve
3	Teach with data, make class engaging, and interact with others	... is interested in learning how to teach students using data and make the class more engaging and interesting for the students and interacting with others in the course	learn, student, statist, data, teach, class, engag, experi, understand, teacher, excit, interest, math, idea, engag_student, student_learn, lot, make, interact, teach_statist
4	Improve teaching/knowledge of statistics by incorporating data and technology	….is interested in learning how to teach statistics, to improve their knowledge of teaching statistics and excited to incorporate interesting data and technologies into the classroom.	statist, teach, learn, student, math, understand, mooc, knowledge, al, improvm teacher, time, data, work, teach_statist, excit, interest, incorpor, technologi, classroom

Table 6 (continued).

Topic	Theme for Motivation	Description This group of participants...	Bag of Words
5	Preparing to teach high school students, particularly AP students	... is preparing to teach high school students this year, particularly AP students, and wants to learn ideas to engage and interest students.	statist, teach, student, year, learn, school, high, high_school, interest, ap, engag, math, understand, taught, teach_statisti, class, teach_ap, engag_student, teacher, idea
6	Looking to get new ideas and resources to prepare for the upcoming year	... is excited to learn to teach statistics for this upcoming year, perhaps AP, and gain new ideas and resources to use in class	teach, statist, student, learn, teach_statist, class, year, stat, time, idea, school, ap, data, mooc, excit, understand, level, resourc, gain

Method 1 Validation

Of the 940 documents that were assigned to a topic for Method 1 (recall 6 documents had a gamma value less than the threshold of 0.5), it was determined that 573 participants' posts, or 61%, were assigned to a topic that seemed appropriate for that collection of posts. Table 7 shows the percentage of times it was determined each document was assigned correctly to a topic. Topic 6 was assigned "Yes" the lowest percentage of the time, with about 50% of the documents applying to the topic assigned, and 50% that were not applicable to that topic. Topic 1 had the highest percentage of agreement, with 70% of the documents assigned to this topic receiving a Yes.

Table 7

Method 1 Topics and Validity Count and Percentages

Topic	Title	Total Documents Assigned Topic	Topic Correct?			
			Yes		No	
			n	%	n	%
1	Teach and understand statistics using data	182	128	70.3%	54	29.7%
2	Preparing to teach new curriculum that uses statistics	155	93	60.0%	62	40.0%
3	Teach with data, make class engaging, and interact with others	168	107	63.7%	61	36.3%
4	Improve teaching/knowledge of statistics by incorporating data and technology	141	87	61.7%	54	38.3%
5	Preparing to teach high school students, particularly AP students	143	83	58.0%	60	42.0%
6	Looking to get new ideas and resources to prepare for the upcoming year	151	75	49.7%	76	50.3%
	Total	940	573	61.0%	367	39.0%

Note. Six users are not included because their gamma value was below the threshold of 0.5.

The following are examples of how topic assignment was given a yes (Y) or no (N) for a participant’s collection of posts. Participant 13262_58 posted the following:

I hold a Masters in Curriculum and Instruction and am completing this course because I despise numbers, despite the fact that I'm quite good with them. ;I tend to face my fears, lol.

Method 1 assigned this document Topic 4, *improve teaching/knowledge of statistics by incorporating data and technology*. This post does not mention anything about this individual wanting to improve their teaching or knowledge of statistics, just that they do not like numbers. Though it may be implied that this person is trying to improve their knowledge of statistics based on this post, every effort was given to apply validation on what was written, not what was implied. So, this topic assignment was given an N. On the other hand, participant 1648_9 posted

Within the past decade, access to data has quadrupled. ;I want to be able to help my students collect, analyze, and present data to solve problems.

This document was also assigned topic 4. This is a valid topic to describe this participant's motivation for being in the course, since they are clearly interested in teaching using data with their students. This was given a Y.

Method 2

Method 2 uses a semi-supervised learning method, seeded topic modeling, to determine the topics specific to motivation identified in the discussion forum posts. For Method 2, qualitative methods were used to first create a list of topics for motivation based on a sample of randomly chosen posts to create a seeded dictionary of topics. These topics were assigned words based on the randomly chosen posts and prior research. This dictionary and the posts were fed into an LDA function that is part of the *seededldapackage* (v0.5.1; Watanabe & Xuan-Hieu, 2020) to then assign each participant a topic from the seeded dictionary (see Appendix I – R Code for Topic Modeling Method 2, Semisupervised with Seeded Dictionary for R code).

Determining the topics for the seeded dictionary

To use the *seededlda* package, a seeded word dictionary had to be made that could be used to feed in predefined topics for the *seededlda* function that is part of the package. The dictionary was created using a priori coding and in vivo coding (Creswell, 2013) to identify themes for motivation based on 10% of the discussion forum posts. Since there were 1,639 original posts from the introductory discussion forums (before the data preparation process described previously), 164 posts were chosen to code to identify motivation themes. These 164 posts by chance were from different participants. The 164 posts were a stratified random sample of the 10 courses based on the percentage of posts to this forum in each course. For instance, course 9 represented 25.5% of the total posts from the introductory forum, so 41 posts were chosen from course 9.

Coding was done using a qualitative coding software, Nvivo (QSR International, 2015). Posts were coded using a priori codes based on the enrollment survey topics. Additional codes were created as the posts were read, using in vivo coding. The a priori and in vivo codes were combined to identify the themes for motivation (topics) as well as words to seed each topic (see

Table 8).

Table 8
The seeded dictionary used for the seededlda function

Topic	**Description** These participants are motivated by….	List of seed words	List of top 10 terms
engaging class	…. a desire to engage students and make class more interesting.	engag*, excit*, appeal*	excited, engage, engaging, exciting, engaged, engagement, appealing, excitement, excite, engages
confidence	….an opportunity to increase their own confidence to teach statistics	confidence, confident, build*	confident, confidence, build, building, builds, like, feel, course, learn, material
repeater	...the desire to take the course again because they had not finished it, or take the second course after already completing the first.	back, attempt, last, second	last, second, back, attempt, year, time, first, course, stats, much
real data	...wanting to learn how to use real data in their practice.	data, real, world	data, real, world, students, using, course, investigations, looking, better, analysis
technology	...wanting to learn how to use technology to teach statistics.	technology, calculator, applet, dynamic	technology, dynamic, calculator, applet, learn, use, statistics, interested, classroom, also

pedagogy	..becoming better at teaching, whether it be specific to statistics or math.	approach, pedagogical, pedagogy, teach*	teaching, teach, teachers, teacher, approach, pedagogical, teaching-wise, teacher’s, statistics, learn

Table 8 (continued).

Topic	**Description** These participants are motivated by….	**List of seed words**	**List of top 10 terms**
stats investigations	...participating in statistics investigations themselves or help guide their students through investigations.	investigation, hands-on, experiment	investigation, hands-on, students, help, course, can, concepts, understand, like, also
student reasoning	...learning how students reason with data or how to help students reason with data	student, think*, reason*	student, think, thinking, reasoning, reason, reasons, ireasoning.e, thinkers, thinks, learning
collaborate	...interacting with other people in the course.	share, community, collaborat*, interact*	share, community, interacting, others, interactive, collaborate, interact, discussions, discussion, collaboration
library of resources	...building a library of resources to use in their own practice.	resources, activities, library, gather*	resources, activities, gathering, gather, gathers, new, ideas, looking, al, get

preparing	...a need to get ready to teach an upcoming course that may use statistics.	common, science, curriculum, class	class, curriculum, science, common, statistics, math, new, classes, one, algebra
professional practice	...the desire to increase their own general professional practice and to earn a certificate of completion.	experience, professional, practice, certificate	experience, professional, practice, certificate, course, education, mathematics, mooc, university, part

Table 8 (continued).

Topic	**Description** These participants are motivated by….	**List of seed words**	**List of top 10 terms**
learn statistics	...the need to increase their statistics content knowledge.	content, knowledge, understanding, statistics	statistics, understanding, knowledge, content, teaching, improve, better, need, gain, really
requirement	...a requirement to take the course, either as part of another course they are taking, required CEUs for their certification, or as part of a PLC.	required, requirement, enroll, renewal, credit	required, renewal, enroll, credit, requirement, school, course, years, stats, college

* indicates that the stem is being used as the term.

There were several iterations of this seeded dictionary. As the dictionary was made, the *seededlda* function was used to assign topics to the sample of posts to help with the process of editing the dictionary. The sample of posts were read to see how close the topics aligned to the actual words in the post. It was found that the more words assigned to a theme, the less likely the post was assigned an appropriate topic. The bag of words assigned to each theme was trimmed to only include 3 - 6 terms. Additionally, when words appear in more than one topic in the seeded dictionary, the function applies the topic where the word first appears. For instance, in an earlier iteration of the dictionary, the term "experiment" appeared in both the topic *realdata* and *statsinvestigations*. But any posts that had the term "experiment" only had the topic *realdata* applied to it instead of *statsinvestigation* even when it was apparent that it was the wrong topic, since *realdata* appeared first in the seeded dictionary. Each term was used in only one topic as determined by the researcher to eliminate this overlap.

Issues with inputting data

The *seededlda* function used in Method 2 requires the input of a document term matrix and a seeded dictionary. Initially, the DTM in the exploratory topic modeling and Method 1 was used as the input. This proved to be problematic. The output from running this function was simply a list of how many times each topic was assigned, instead of an output of which participant is identified with each topic. After contacting the lead author of the *seededlda* package, Kohai Watanbe, a solution was found.

Instead of defining the DTM as it was for Method 1, a data frame was made with a list of rows of two variables *userid* and *post*. The userid was the list of participants in the cleaned data set, and post was the merged posts that were used for Method 1. Then two functions in the *quanteda* package (Benoit, et al., 2014), *corpus* and *dfm* were used to turn this data frame into a document feature matrix (DFM), another acceptable input for the *seededlda* function. Like the DTM from Method 1, the DFM has the rows of the matrix as the participants and the columns are all the words that appear in the corpus of posts. Each cell is the number of times that word appears for each participant (see

Figure 9).

Figure 9

Image of the first few rows and columns of the DFM

	as	i	get	closer	to	graduation	,	am	seeking	enhance	my
10014_52	1	2	1	1	4	1	1	1	1	1	4
10040_40	0	2	0	0	2	0	1	2	0	0	3
10168_52	0	2	1	0	4	0	1	1	0	0	1
10168_76	0	0	1	0	1	0	0	0	0	0	0
10185_52	4	9	0	0	5	0	5	0	0	0	4
10204_52	0	2	0	0	2	0	0	1	0	0	2
10215_52	0	0	0	0	0	0	0	0	0	0	0
10221_52	1	1	0	0	2	0	2	0	0	0	2
10223_52	0	1	0	0	2	0	1	0	0	0	1
10225_52	0	4	0	0	5	0	0	2	0	0	0
10225_76	0	6	0	0	3	0	1	1	0	0	1
10248_52	0	1	0	0	1	0	0	1	0	0	1
10280_52	0	3	0	0	2	0	2	1	0	0	1
10290_52	0	1	0	0	3	0	0	1	0	0	2
10301_52	0	1	0	0	2	0	1	0	0	0	0
10334_52	0	3	0	0	4	0	1	1	0	0	1
10344_52	0	5	0	0	5	0	2	0	0	0	4
10344_76	1	2	0	0	4	0	2	2	0	0	2

For Method 2, the stop words and stemming were not applied to the DFM as they were in the DTM for Method 1. Instead, stemming was applied in the seeded dictionary. In

Table 8, wherever a word has a *, indicates that all words with that stem should be part of that topic. Stop words were also not removed since they do not pose the problem in this function as they do the function used in Method 1 because of predefining the topics in the seeded dictionary (K. Watanabe, personal communication, March 17, 2021).

Identifying and validating topics

To assign the topics for Method 2, the *textmodel_seededlda* function in the *seededlda* package was used. This function requires an input of the seeded dictionary that was created (see

Table 8) and the DFM created (see Figure 7). The function assigns each topic to a user based on the frequency of times the words appear in the DFM like the LDA function used in

Method 1. The number of topics is defined by the number of topics in the seeded dictionary. The *textmodel_seededlda* function has an option to have one automatic *other* topic created as well as the predefined topics. This *other* category is applied to documents that do not meet the criteria of the function. After applying the function initially with this option chosen, it was found out that only 3 of the 48 documents that were assigned the *other* topic seemed to not relate to the other 14 topics. Thus, the option of having an *other* topic was not used here and instead all documents were assigned one of the topics in

Table 8.

The *seededlda* function returns a list of words that define each topic. This will include the seed words from the dictionary as well as other words that fit into the theme based on the likelihood that each topic produces each term (Watanabe & Xuan-Hieu, 2020). The *seededlda* function only returns this list of terms for each topic. To determine which topic was most likely applied to each user, the output for the *seededlda* function was assigned a name (in this case *userid_bycourse*) from the DFM created previously (K. Watanabe, personal correspondence, February 13, 2021). This forced the program to create a table with each user and each topic most likely associated with that participant's document (or collection of posts).

Like Method 1, the researcher read the merged posts for each user and determined whether the topic assigned by the *seededlda* function was appropriate based on the description of that topic in

Table 8. The results of this validation process were recorded for the overall posts as well as for each topic.

Method 2 Topics and Validation

Table 9 shows the number of documents (participant's collection of posts) that were assigned to each topic for Method 2. Table 9 also shows the number and percent of valid assignments for each topic. There were 14 topics created in the seeded dictionary using the terms shown in

Table 8. Of the 946 documents, 463, or 48.9%, were considered to have an appropriate topic assigned to them by Method 2. Additionally, 483, or 51.1%, were not considered to be assigned

to an appropriate topic. The topics with the highest agreement were *preparing* (72.2%), *collaborate* (71.6%), and *library of resources* (68.7%). The topics with the lowest agreement were *requirement* (21.3%), *stats investigations* (26.2%), and *repeater* (28.4%). These examples showcase the wide range of percentages that appeared in the 14 topics created under Method 2.

Table 9
Method 2 Topics and Validity Count and Percentages

Topic	Title	Total Documents Assigned Topic	Topic Correct?			
			Yes		No	
			n	%	n	%
1	library of resources	99	68	68.7%	31	31.3%
2	collaborate	88	63	71.6%	25	28.4%
3	repeater	88	25	28.4%	63	71.6%
4	students reasoning	78	25	32.0%	53	68.0%
5	learn statistics	73	37	50.7%	36	49.3%
6	confidence	71	29	40.9%	42	59.1%
7	engaging class	67	27	40.3%	40	59.7%
8	requirement	61	13	21.3%	48	78.7%
9	pedagogy	60	38	63.3%	22	36.7%
10	technology	59	24	40.7%	35	59.3%

Table 9 (continued).

Topic	Title	Total Documents Assigned Topic	Topic Correct?			
			Yes		No	
11	professional practice	58	35	60.3%	23	39.7%
12	preparing	54	39	72.2%	15	27.8%
13	real data	48	29	60.4%	19	39.6%
14	stats investigations	42	11	26.2%	31	73.8%
	Total	946	463	48.9%	483	51.1%

The following are examples of documents and their assigned validity for the topics above. Participant 11997_58 posted:

Statistics is not a strength of mine. I do not want my students to struggle because their teacher struggles with concept.

Method 2 assigned this document to Topic 4, students' reasoning. Since the post includes the word *students* it makes sense why the assignment was made, but this participant is clearly struggling with their own confidence, not with how students are reasoning with statistics. This post was given an N for not correctly identifying a topic.

Participant 9678_58 posted the following,

Each year I become more acutely aware of all that I don't know about teaching stats, as opposed to just knowing how to think like a statistician. I know I've trained my kids to be good test-[take]rs of the AP Statistics exam, but does that necessarily equate to statistically literate college freshmen, ready to apply their learning in their chosen fields of study?

This document was assigned Topic 4 as well, student reasoning. This participant clearly is concerned with strengthening their students' statistical reasoning skills beyond that of just preparing for the AP Statistics exam (a common theme among participant threads). This document was assigned a Y, as it seems valid that this participant is motivated to strengthen their students reasoning.

Method 3

Method 3 uses the same topics as Method 2 but collapses the topics into more general topics that combine topics in Method 2. When assessing the validity of the topics assigned for Method 2, it was found that the percentage of topics correctly assigned was much lower than Method 1. The number of overall topics in Method 2 was considerably higher than Method 1 (14 topics versus 6), which could have led to the lower validity rate. Method 3 is an attempt to create general topics based on the topics from Method 2.

Method 3 Topics and Validation

The topics from Method 2 (see

Table 8) were collapsed into four topics (see Table 10). Recall the LDA tuning package that was used in Method 1 determined that between four to six topics is an ideal number of topics for this data. The first theme to combine goals was to group goals by *course specific goals*. When enrolling in a course, participants could see the course objectives, so we assumed that some people were motivated by the goals they saw prior to enrollment. The second theme was to collapse goals that are specific to *continuing professional learning*. Since these courses give people the opportunity to earn continuing education credits, we assume that some people may enroll for professional learning goals outside of specific course goals or take a course again. Another common theme in discussion forums is for participants to want to become better teachers, hence the third theme of *pedagogical goals.* The final theme was for participants who want to *learn statistics/increase confidence*. These could be separate themes, but it was found they often occur together. We recognize that other groupings may have been appropriate, but these topics were collapsed based on the researchers' prior experience with the data.

Table 10
Topics for Method 3. These topics were collapsed from those in Method 2.

Topic	**Theme for Motivation**	**Topics that were collapsed together from Method 2**	**Description** These participants are motivated by….
1	Course specific goals	real data, technology, stats investigation, students reasoning, library of resources collaborate	...goals that are listed specifically in the description of the courses.
2	Continuing Professional Learning	professional practice, requirement, repeater	...continuing their general professional practice, including earning CEUs, taking the course as a requirement, or taking/retaking a course after being previously enrolled.
3	Pedagogical goals	engaging class, preparing, pedagogy	...learning materials in the course that will make their classes more engaging, preparing to teach statistics in an upcoming course, or increase their general pedagogical skills.

4	Learn Statistics/ Increase Confidence	learn statistics, confidence	...either learning statistics or increasing their confidence to teach statistics.

Whichever topic a participant was originally assigned in Method 2 carried over to Method 3. Then each of those topics was renamed to the appropriate topic in Table 10. If the topic applied to the participant in Method 2 was valid, it remained valid in Method 3. The participant documents that were not considered valid were then reassessed for the validity based on the collapsed topics in Method 3. The results of the assigned topics and validity can be found in Table 11.

The validation process for Method 3 was like Methods 1 and 2. Each of the documents that were assigned an N in Method 2 were then read again to see if the topics from Table 10 were appropriately assigned for Method 3. For instance, participant 4726_76 wrote:

The downside to being a private school, is that I don't have other math teachers in the building or a district to collaborate with about statistics. The good news is that I have found these courses to be excellent in filling in those gaps!

Method 2 had assigned this document to the topic, *student reasoning*. It was given an N in the validity score of Method 2. This is clearly not applicable to that topic because nowhere in this post does the participant mention students much less anything about how students reason. For Method 3, *student reasoning* falls under topic 1, *course specific goals*. Based on a qualitative interpretation, this participant's main goal is to collaborate with others during the course since they do not have this opportunity at their own school. Collaboration among other teachers is also an explicit course specific goal, and more closely describes the theme of this document. Thus, for the validity of Method 3, this post received a Y, but if collaboration had been collapsed into a different topic (such as continued professional learning), then this post would not been correctly assigned to course specific goal.

Table 11
Method 3 Topics and Validity Count and Percentages

Topic	Title	Total Documents Assigned Topic	Topic Correct?			
			Yes		No	
			n	%	n	%
1	Course specific goals	414	367	88.6%	47	11.4%
2	Continuing professional learning	207	113	54.6%	94	45.4%
3	Learn statistics/increase confidence	144	81	56.3%	63	43.7%
4	Pedagogical goals	181	156	86.2%	25	13.8%
	Total	946	717	75.8%	229	24.2%

Table 12
Summary of 3 Topic Modeling Methods

	Method 1	**Method 2**	**Method 3**
Topic Modeling Method used	Unsupervised learning method	Semi-supervised learning method	Semi-supervised learning method with topics collapsed to general themes aligned with goals listed on registration survey
R function	*LDA* function in *topicmodels* package	*textmodel_seededlda* function in *seededlda* pacakge	same as Method 2
Inputs for function	Document term matrix comprised of user identified discussion posts	Document frame matrix of user identified discussion posts and a seeded dictionary of topics	same as Method 2
Number of topics	6	14	4
Overall validity rate (% of documents assigned a valid topic)	61.0%	48.9%	75.8%
Validity rate range among individual topics	49.7% - 70.3%	26.2% - 71.6%	54.6% - 88.6%

Of the 946 documents, 75.8% were determined to be assigned to an appropriate topic and 24.2% were not assigned to an appropriate topic. The topics with the highest validity score were *course specific goals* (88.6%) and *pedagogical goals* (86.2%). The other two topics had considerably lower validity scores, *continuing professional learning* (54.6%) and *learn statistics/increase confidence* (56.3%).

Discussion

This study sought to determine in what ways topic modeling can be an effective tool for identifying motivation in discussion posts. The introductory discussion posts in these two courses proved to be a rich source of data to identify themes of motivation for enrolling in these courses. After data cleaning and combining participants' posts into a total of 946 documents, three methods for topic modeling were used to identify themes for motivation to enroll in online professional development courses for statistics teachers. The documents were then read to see how closely the topics assigned for each method aligned to a particular participant's set of discussion posts. The results of the three methods used in this study are found in

Table 12.

The goal of this study was not to determine which method was better at assigning topics to the discussion posts. If that were the goal, then we could say that Method 3 is "best" since it has the highest validity score. It is of interest that Nelson et al. (2021) found that the dictionary-based method they used was also not the most aligned to hand-coded data, suggesting "dictionary methods will struggle with the identification of broader concepts but can play a role when specific phrases are of interest" (p. 228). In our study the dictionary-based method only did better after collapsing the terms.

The use of the validity score is like using an interrater reliability (IRR) measure that is common in qualitative research. But even among qualitative researchers, the use of and application of an IRR measure can be controversial (Hammer & Berland, 2014; McDonald, et al., 2019). There are also different ways to measure IRR. What is referred to as validity in this study is a simple percent agreement measure between the primary researcher and the topics applied by each method. Though the validity measure here (and any IRR measure) is helpful to evaluate the consistency of the topic applications from these methods, it cannot be a substitute for making meaning from the data (McDonald, et al., 2019). Qualitative researchers must be careful in pursuing a coding scheme based on reliability and validity of the coding between researchers, if that scheme does not give an accurate representation of the data (Hammer & Berland, 2014).

Instead, the goal of this study was to investigate how topic modeling can be used for analyzing qualitative data, particularly analyzing the motivation of participants to enroll in online professional development for statistics teachers using discussion forum data. By comparing the different topic modeling methods to qualitative analysis results, this study suggests that topic modeling can be a useful tool for qualitative researchers in their analysis process. Analyzing qualitative data is a "process of bringing order, structure, and meaning to a mass of collected data" (Marshall & Rossman, 1990, p. 111). Though qualitative data analysis often produces rich and informative results, the process can be tedious, time consuming and messy (Creswell, 2013; Hilal & Alibri, 2013). This has become even more true now that large data is available, such as discussion forum data in MOOCs.

In this study, Method 1 was used to identify themes for motivation using a computer algorithm, rather than researchers reading every post to identify themes. Though the validity score for Method 1 was not very high (61%) the themes identified gave good insight into why people enrolled in these courses, outside of the choices they indicated on an enrollment survey. Though there are certainly themes for motivation that did not arise with this method, there are probably themes that are also missed in any traditional qualitative analysis approaches. Another researcher may be able to use this same methodology on a large collection of data to identify initial themes, and then follow through with traditional qualitative coding methods.

Method 2 and 3 used a semi-supervised learning method to identify themes for motivation. Instead of interpreting themes that arose from an unsupervised learning method, like Method 1, Method 2 and 3 required the input of a seeded dictionary. This dictionary was created by using identified themes for motivation from a subset of the discussion forums, then applied to the entire data set. This is not unlike traditional qualitative methods, where a group of researchers may code a subset of the data, identify, and define themes, then create a “codebook”, and apply those codes to the rest of a dataset (Roberts et al., 2019). In this case, the primary researcher created a codebook with the seeded dictionary, then let the computer algorithm *code* the remainder of the data. This semi-supervised learning method is particularly useful when there is a lot of data, but not a lot of research capacity (i.e., people hours) to apply the codes to a large dataset. Though the validity scores for Method 2 was very low (~49%) the validity for Method 3 (after collapsing codes in Method 2) rose to approximately 76%.

Limitations and Future Work

Several limitations to this study should be taken into consideration. The authors limited topic modeling techniques used because of the use of R as the primary coding software for analysis. Many other topic modeling techniques exist in and out of the R community. This study only used the *topicmodels* and *seededlda* packages in R. The set of discussion forum posts that were used as the data set only included the text that was included in the discussion forum. There were times that participants posted pictures, added hyperlinks, or used other html inputs, such as emojis, that were not part of the forum data that was analyzed. Any themes for motivations that may have been in this qualitative data were not considered as part of this study.

The Porter stemmer method was used to stem words in the creation of the document term matrix that was used in all three topic modeling methods used in this study. The Porter stemmer method is susceptible to over-stemming words or causing faulty conflation of words (Farrar & Hayes, 2019; Krovetz, 1993), meaning that words seem to appear more often only because they were shortened so much. There are other methods that could have been used, such as the Krovetz method which attempts to help this over-stemming process but is also known to under-stem words (Farrar & Hayes, 2019). This study acknowledges the limitations of the Porter method in the data cleaning process of the discussion forum data. Future research could explore other methods.

This study is part of a larger study that analyzes the motivation and engagement of participants of the online professional development courses identified in this study. Motivation is identified using responses in an enrollment survey that participants completed before they started the courses. It was hypothesized that topic modeling could also be used to identify other motivational factors beyond the enrollment survey responses for participants that posted in the orientation discussion forum. Future research with this data will use the combined motivational factors and engagement data collected from click-log data of participants while they took the course to identify clusters of participants, based on their motivation for taking the courses and how they engaged in the courses.

Conclusion

Isoaho et al. (2021) state that when a topic model is applied to a data set, three steps need to be followed to ensure the reliability of the model.

> First, the output of the model needs to be interpreted. Second, the choice of preprocessing and modeling parameters needs to be validated. Finally, the ability of the topics to model the phenomenon under investigation needs to be evaluated. (Isoaho, et al., 2021, p. 306).

They go on to state that many studies that employ topic modeling methods do not follow these procedures and proceed to interpret the results of the topics in isolation from the documents that were used to produce the topics. This study did not make that mistake. The topics produced and validity of the model were interpreted and evaluated with the data of the discussion forums always present in the process. We assert the context of the data used to produce topic models must always be the biggest consideration when interpreting and sharing the results.

Ability to replicate a study is often hard to do for any qualitative analysis, since researchers do not often share the steps of how codebooks are made or how thematic coding is applied (Roberts, et al., 2019). It is the hope that enough detail is provided in this article so that the topic modeling methods can be replicated and hopefully built upon so that topic modeling can become a useful tool in the world of analyzing large amounts of qualitative text data.

CHAPTER 5 MOTIVATION AND ENGAGEMENT OF PARTICIPANTS IN ONLINE PROFESSIONAL DEVELOPMENT COURSES FOR STATISTICS EDUCATORS: A CLUSTER ANALYSIS APPROACH

Journal

This chapter presents a journal ready manuscript to be submitted to *Computers and Education*. This journal seeks to increase knowledge and understanding of how digital technology can enhance education. The editors welcome research articles on the pedagogical use of technology, particularly papers that may be of interest to a wider education community. This manuscript will be submitted as a research report, that describes original empirical research. Research papers should be no longer than 8,000 words in length, excluding references and appendices. This journal also requires authors to submit "Highlights". Highlights are a list of bullet points of the novel results and new methods that were used. These highlights are meant to help the article be more discoverable by search engines. *Computers and Education* also encourages the sharing of data and coding that were used in the research to promote the reproducibility of novel methods. I will prepare the data and coding used in creating the clusters in this research as appendices.

Abstract

The need for professional development (PD) for teachers of statistics has risen over the last decade due to the increase of statistics standards in mathematics curriculum, though providing high quality PD for these teachers can be a challenge. Fortunately, there are free Massive Open Online Courses for Educators (MOOC-Eds) that can be a convenient and timely way for those who teach statistics to find resources to help their instruction, and a community of educators with similar interests. The open nature of MOOCs has led to research in what motivates participants to enroll in these courses as well as how they engage with the course materials. Understanding motivation and engagement of participants can help inform the creation of similar resources for educators. This study investigates two successive online courses for teachers of statistics that were offered a total of 10 times from 2015 – 2019. Topic modeling of introductory discussion forums revealed four motivating themes for enrollment, while cluster analysis using enrollment survey data (closed-ended goals) and these topic modeling themes (self-stated goals) was used to group participants into three clusters based on motivation. Additionally, cluster analysis using click-log data grouped participants into three clusters based on their engagement. It was found that there was no relationship between motivation and engagement based on these clusters when analyzing all participants. But when looking particularly at participants who took both courses, those with higher engagement tended to be the ones who were motivated by goals of the course(s).

Keywords: Teacher Professional Development, Adult Learning, Distance Education and Online Learning, Human-computer interface, Data science applications in education

Introduction

The incorporation of statistics into mathematics curriculum has been on the rise in the past decade, with the adoption of Common Core Mathematics Standards that include statistics standards that start in 6th grade then continue through high school mathematics (CCSSM, 2010). There has also been an increase in enrollment in AP statistics courses over the past decade, as well as a reconceptualization of how statistics is taught at post-secondary institutions (Carver, et al., 2016). This rethinking of how statistics is taught has led the American Statistical Association (ASA) to create guiding frameworks for best practices for teaching statistics in K-12 mathematics curriculum (Franklin, et al., 2007), as well as introductory statistics courses at the collegiate level (Carver, et al., 2016). Unfortunately, there are many pre-service and in-service teachers who feel underprepared to teach these statistics standards (Lovett & Lee, 2017). In response to this need, the ASA created the *Statistical Education of Teachers* (SET) report to guide universities in preparation of pre-service mathematics teachers to teach statistics, as well as put out a call to districts to provide professional development (PD) for in service teachers who are required to teach statistics (Franklin, et al., 2015).

There are challenges to providing high quality PD for teachers of statistics. Oftentimes statistics teachers may be the only one in their school, or even their district who teach statistics, so they may have to travel far to find PD specific to statistics (Franklin, et al., 2015). Teachers often have other demands that may make finding time to engage in face-to-face PD challenging. Online professional development (OPD) can be a way to address these challenges while helping teachers learn the skills and knowledge, they need to effectively teach statistics (Lee & Stangl, 2015). Massive open online courses for educators (MOOC-Eds) have been created specifically for teachers of statistics (Hollebrands & Lee, 2020; Lee & Stangl, 2015).

MOOC-Eds are free open courses, which means that anyone with the internet can enroll in the course and participants can engage in the material however they want. Like most MOOCs, this open nature has challenges in evaluating course participation and success. Instructors often do not know much about who is in the course and why, and there are no penalties or consequences for not being engaged in any part of the materials (Douglas, et al., 2020). Additionally, success does not have to be measured by completing a course or obtaining a certificate of completion, since some people may simply be there to observe the course. For these reasons, it is important for those developing open online courses to know the reasons why people enroll in courses and how they engage in the courses. These findings could prove useful to others creating similar OPD courses.

This study attempts to describe the motivation and engagement of participants in two successive OPD courses for statistics educators. Motivation clusters are identified from responses in an enrollment survey and results of topic modeling in an introductory discussion forum. The topic modeling results are shared in this paper, but the methods of the topic modeling procedure were a part of a past study (Authors, under review). Engagement clusters are identified using cluster analysis of click-log data collected from participants in these two courses. These findings are combined to see if motivating factors are related to how participants engage in the course. The following research questions will be addressed:

1. What motivates participants to enroll in online professional development courses for statistics educators?

2. How do participants of OPD for statistics educators engage in the courses?

3. How is motivation for enrolling in OPD for statistics educators related to how participants engage in the course(s)?

Background Literature

The section begins with an overview of the need for professional development (PD) for teachers of statistics, followed by specific PD efforts to answer that need. Online professional development (OPD) efforts for statistics educators will be highlighted. The next section will give an overview of research efforts to determine what motivates participants to engage in online learning as well as how they engage in online learning.

Professional Development for Teachers of Statistics

The inclusion of statistics in the K-12 mathematics curriculum has led many colleges and universities to re-examine how to incorporate statistics into mathematics teacher preparation courses (Carver et al., 2016), which has led to efforts to increase PD for in-service teachers to teach statistics. Often pre-service mathematics teachers may be required to take as many as four calculus courses, but most secondary mathematics teacher programs only require one statistics course (Franklin, et al., 2015). Mathematical and statistical thinking are different (Cobb & Moore, 1997), and if pre-service teachers are not getting the preparation they need to confidently teach statistics (Lovett & Lee, 2017), then there is a need for offering wide-scale professional learning opportunities for in-service teachers. To increase students' statistical thinking, "robust professional development opportunities need to be developed for advancing in-service teachers' understanding of statistics" (Franklin, et al, 2015, p.6). Though Franklin et al. realize the need for PD specific to statistics education, they also admit the limitations of providing these sorts of opportunities at local levels (Franklin et al., 2015).

Recommendations for subject matter to include in PD to promote statistical thinking include developing a deep conceptual understanding of statistics instead of just performing statistical procedures (Franklin et al., 2005), actively engaging in the statistical investigation cycle (Franklin et al, 2015), and keeping educators current with technology for conducting statistical investigations (Biehler et al, 2013; Pratt et al., 2011). PD efforts focused on fostering deep conceptual understanding of statistics have showed increased understanding among teachers of concepts, such as measures of center and measures of variation, that they had often overlooked (Peters, et al.2014; Peters & Stokes-Levine, 2019), though some PD efforts found teachers did not foster deeper conceptual understanding after the PD (Kuzle & Biehler, 2015). It has been found that those teachers who attend PD where they engage in the statistics investigation cycle tend to better support their own students in statistics investigations (Makar & Fielding-Wells, 2011; McClain, 2009; Souza et al., 2015). PD that prepared teachers to use current statistics technology, such as dynamic statistical software, empowered teachers to use the technology in their own classrooms (Madden, 2014; Wassong & Biehler, 2014)

Professional development like those shared above have proven effective in increasing statistical thinking among teachers, but online professional development (OPD) with similar goals may prove to be more convenient and timelier to those that do not have access to local seated PD. Though there have been blended online PD opportunities, where part of the experience is face to face and part is online (Akoğlu, 2018; Akoğlu, et al., 2019; Wassong & Biehler, 2014), there have been far fewer *fully online* PD experiences for teachers of statistics. OPD courses for in-service statistics teachers have been a source of increased statistical understanding and can provide a source of community among statistics educators (Garfield & Everson, 2009; Meletiou-Mavrotheris, 2011).

Other fully online PD include MOOC-Eds (Massive Open Online Courses for Educators) that focus on statistics pedagogy (Lee & Stangl, 2015). Stangl and her team developed the *Teaching Statistical Thinking* MOOC that begins with an introduction of descriptive statistics, lessons on implementation of descriptive statistics in the classroom, followed by a focus on software that can be used for descriptive statistics (Lee & Stangl, 2015). Lee and her team created two MOOCs titled *Teaching Statistics through Data Investigations (TSDI)* and *Teaching Statistics through Inferential Reasoning (TSIR)*. Each course is meant to enhance teachers understanding of statistics and teaching strategies in middle school classes through introductory level college courses. TSDI and TSIR are the focus of the current study.

Motivation and Engagement Research in Online Learning

The rise of Massive Open Online Courses (MOOCs) has led many researchers to explore participant motivation for enrolling in a course, as well as patterns of engaging in course materials (Frankowsky, et al., 2015; Perna, et al., 2014; Thompson, et al., 2016; Wilkowski, et al., 2014). For curriculum developers and course instructors, "the goal for curriculum development has typically been to create a linear sequence of content in an optimal order of increasingly complex content," but online learning courses are more flexible (Wiebe & Sharek, 2016, p.55). This new kind of course design attracts a diverse group of learners with varying goals to MOOCs. Because of this diversity, models for motivation can and should be linked to patterns of engagement that emerge for participants in these courses (Thompson, et al., 2016). This section presents a general model of engagement and motivation as well as prior research on motivation and engagement in online learning, specifically MOOCs.

The work of this study, and of the many researchers trying to understand the connection between motivation and engagement, especially in online learning, is situated in a general model of engagement. Wiebe and Sharek (2016) state that there is no one unified model of engagement, but they explore many well-established psychological models that have been used to understand engagement. Each of these models is linked to a sequential model they call the *General Model of Engagement* (Figure 10). This model shows that engagement is at the center of motivation and learning. To understand engagement, we must first understand the goals and decisions that bring individuals to the point of engaging in effortful tasks, such as engaging in OPD.

Figure 10

General Model of Engagement (Wiebe & Sharek, 2016)

Self-determination theory can help in understanding engagement and motivation by exploring the conditions that motivate humans to initially engage in challenging tasks (Wiebe & Sharek, 2016). According to self-determination theory, motivation can come from intrinsic or extrinsic influences and factors. Intrinsic motivation is when an individual may pursue a task for the sheer human pursuit of learning or creativity and extrinsic motivation comes from outside influences or rewards that require the completion of a task (Eccles & Wigfield, 2002; Wiebe & Sharek, 2016). Earning a certificate of completion is often a source of motivation for enrollees, though researchers have agreed that earning a certificate of completion or *finishing* a MOOC is not the only measure of participants' success (Wilkowski, et al., 2016). This is especially true for MOOC participants that are already highly educated and may not need to earn a certificate of completion (Bonafini, 2017; Emanuel, 2013; Hollebrands & Lee, 2020). Other sources of motivation may also arise such as participating in a MOOC to be part of a social group (Moore & Wang, 2020; Wiebe & Sharek, 2016).

Identifying motivation for enrolling in a MOOC is often achieved by asking questions on enrollment surveys (Creager, et al., 2018; Hollebrands & Lee, 2020; Moore & Wang, 2020; Wilkowski, et al., 2014). Wilkowski et al. (2014) found that the only goals that were met at least 50% of the times by participants were those that were satisfied after engaging in the first one or two units of the course. Similar results have been used by MOOC developers as the reason for placing the most important materials early in the course (Hollebrands & Lee, 2020). Moore & Wang (2020) used latent profile analysis to classify participants of a MOOC by two profiles, intrinsic or extrinsic learners. They found that those who were grouped as intrinsic learners tended to have higher rates of completion, despite the fact those identified as extrinsic learners were most likely to be enrolled to earn a certificate of completion. Moore and Wang (2021) completed another study where they used latent profile analysis to group people using gender, education level, reasons to register, and motivation (extrinsic or intrinsic) to analyze their performance. They again found those driven by intrinsic motivation, as well as females, tended to perform better.

The open nature of MOOCs has led many educational researchers to analyze participant engagement in the courses. Being able to measure and describe engagement can help inform course design for future course developers (Thompson, et al., 2016), be used to describe clusters of participants by engagement (Frankowsky, et al., 2015), or help with the creation of technology that can give real time feedback to participants on their progress towards meeting their goals (Wilkowski, et al., 2014). It has been found that though most MOOCs do not require participants to progress sequentially through a course, most choose to do so (Lee et al., 2018; Perna et al., 2014). Perna et al. (2014) also found no significant engagement factors that could be used to predict successful course completion.

Wiebe, et al. (2015) argue that research in engagement in MOOCs needs to move past descriptive statistics such as those used in the Perna, et al. (2014) study, and move toward a more person-centered approach. A "person-centered approach does not assume that the effect of a given variable is linear, and it accounts for many complex interactions with other variables in a model" (Wiebe, et al., 2015, p. 253). Cluster analysis is one such person-centered exploratory analysis method that can be used to classify participants into clusters, or groups, when a classification of groups is not known (Frankowsky, et al., 2015). Cluster analysis was used to group participants of a MOOC-Ed into different clusters based on their engagement with resources over time (Frankowsky, et al., 2015; Wiebe, et al., 2015).

Prior Motivation and Engagement Research of TSDI and TSIR

Prior research of the courses of this study, TSDI and TSIR, has investigated the three parts of the general model of engagement (motivation, engagement, and learning) to understand what brings people to the courses as well as investigating how they engaged in the courses. Prior research has also investigated what participants have learned, based on surveys and interviews. This section will focus on motivation and engagement research since that is the focus of this study. Though, it is our intent to extend the results here to explore what participants have learned after participating in the course.

Hollebrands and Lee (2020) analyzed participants in three OPD courses for mathematics and statistics educators (two of which were TSDI and TSIR) offered between September 2015 and May 2019 (14 total offerings, 7 were TSDI and 3 were TSIR). They found that in the enrollment survey, of those that responded to a question asking about their reason for enrolling in the course, 44.8% enrolled to deepen their understanding of course content and 35.1% enrolled in the course to collect resources and tools to use in their own practice. Other motivating factors for enrollment have not been fully explored.

Click-log data from the courses has been analyzed to provide a rich description of how participants have engaged with the materials. Lee et al. (2017) and Mojica et al. (2018) used click-log data to examine engagement trends in TSDI offerings. They found that participants that opened Unit 1 had a higher completion rate than traditional MOOC courses. Tran and Lee (2016) analyzed click-log data from the Spring 2015 course offering to categorize participants into three categories. *No shows* were those that never entered the course after registration, *visitors* were those that logged in and engaged with materials four or fewer times, and *active participants* were the rest. Tran and Lee (2016) and Bonafini (2018) also acknowledged a group of participants identified as *lurkers*, those that read discussion forums but never actually posted to the forums. Though it has been hypothesized that lurkers probably gained something from participating in the courses, there has been no research to identify what they have learned in TSDI or TSIR.

Beyond engagement with materials, research has also focused on how participants in these courses engage with one another. Bonafini (2018) used the social theory of learning (Wenger, 1998) and connectivism (Siemens, 2004) to describe the nature of interaction between participants in the Fall 2015 TSDI course offering. Bonafini (2018) identify 4 individuals identified as *super-posters,* these individuals alone posted 10% of all total posts in the course. Barker and Lee (2018) identified a group of eight highly active participants that took TSDI and TSIR in succession. These participants were leaders in discussions and helped further the topics in the forums where they posted.

The current study will build on this previous research of motivation and engagement of participants. Motivation has not been fully explored in these courses beyond some initial findings in the enrollment survey. Engagement has been explored, but not in a “person-centered” approach suggested by Wiebe et al. (2015). Also, of note is that the previous work did not include data from all 10 course offerings of TSDI and TSIR. This study will present findings from all 10 courses, offering a more complete view of the participants.

Methods

Course Context

This study is bounded by the online environment of two successive online professional development courses, *Teaching Statistics through Data Investigations* (TSDI) and *Teaching Statistics through Inferential Reasoning* (TSIR), and educators who choose to participate in the course(s). These courses are hosted by the Friday Institute for Educational Innovation through their learning platform The PLACE: Professional Learning and Collaboration Environment. Both courses were developed by two teams led by Dr. Hollylynne Lee of NC State University, Professor of Mathematics and Statistics Education. The PLACE is a website (place.fi.ncsu.edu) that provides free resources to educators for PD, including MOOC-Eds, blending learning opportunities, micro-credentials, and teaching resources.

TSDI and TSIR were intended to attract educators in middle grades to college, interested in strengthening their statistics pedagogy. The “overarching goal of [TSDI] is to engage participants in thinking about statistics teaching and learning in ways that are likely different from their current practices in middle school through college-level introductory statistics” (Lee, et al, 2020, p. 4). Participants in TSDI were introduced to the *Students Approaches to Statistical Investigations (SASI)* framework, which incorporates the four phases of the statistical investigation cycle (pose, collect, analyze, interpret), statistical habits of mind, and different levels of statistical sophistication (Lee & Tran, 2015). TSIR was meant to be an extension of the materials in TSDI while emphasizing inferential reasoning. The courses consisted of five units and an orientation unit.

TSDI was taught seven times through The PLACE, with the first offering in the Fall of 2015 and the last in the Fall of 2018. TSIR was offered three times, in Fall 2017, Spring 2018 and Spring 2019. The courses were asynchronous, meaning that participants were able to complete course work at their convenience; they were not required to log in to the course at a pre-determined time.

Participants

In the seven offerings of TSDI there were a total 3,115 participants registered for the course. In the three offerings of TSIR there were a total of 700 participants registered for the course. The primary audience for TSDI and TSIR are grade 6-12 teachers and post-secondary teachers who teach statistics, though it attracted professionals in other disciplines. Both courses have drawn a variety of participants with a variety of different backgrounds, but most participants are classroom instructors. There have been participants enrolled from all 50 states and over 84 countries worldwide. The courses were asynchronous, meaning that participants were able to complete course work at their convenience; they were not required to log in to the course at a predetermined time.

Participants in this study are those individuals that accessed at least Unit 1 of at least one course. Of the 3,815 total people that enrolled in either course, 1,592 accessed at least Unit 1 of a course. Researchers have found a high drop off rate of participants after the first unit of MOOCs (Erikkson, et al., 2017; Hollebrands & Lee, 2020; Onah, et al., 2014). This likely indicates that participants visited and found they were no longer interested in the course or no longer had the time to participate. For these reasons, only those who participated in at least Unit 1 (1,592 participants) are included in this study.

There are participants who enrolled in more than one course offering. These may be individuals that initially engaged in a course and did not complete it, and later enrolled in another offering. Or they are individuals who enrolled in either TSDI or TSIR, then decided to take the other course. Since motivation and engagement can change over time, it was decided to treat each time a person took a course as a separate participant. Thus, participants are identified using their numeric user identification number *and* course identification number (userid_bycourse). Of the 1,592 unique participants there were several instances of people enrolling in more than one course. All together there are 1,949 participants for analysis purposes, of which 1,592 are different people.

There are instances when an individual may have enrolled in a course and not participated in Unit 1 of that course but enrolled in another course offering and did participate in Unit 1. All instances of an individual's participation were kept for analysis (if they engaged in Unit 1 of at least one course), since these participants are part of a larger project analyzing engagement and motivation. For the remainder of this paper, the term participant refers to a participant who is enrolled in a specific course and accessed at least Unit 1 of at least one of the 10 course offerings in this study.

Registration data was used to describe the 1,592 unique participants. All states in the United States are represented, with 1,271 participants from the U.S. There are a total of 73 countries represented, with the New Zealand (n = 60), United Kingdom (n = 26), Australia (n = 20), India (n = 20), and Canada (n = 17) having the next highest enrollment. Of these participants more than half reported they were classroom teachers (62.0%), 65.9% identified as female, and 79.0% had advanced degrees (masters or doctoral degrees).

Sources of Data

The sources of data for this study fall under two categories, data for motivation and data for engagement. The data used to analyze participant motivation to enroll in a course was discussion forum data and enrollment survey responses. The data for engagement is click-log data that was collected on each participant as they engaged with material in each course.

Motivation Data

Two types of goals were used as motivation data, self-stated and closed-ended goals. Self-stated goals were determined from a prior study that used topic modeling to identify themes for motivation in the introductory discussion forum. Closed-ended goals were goals chosen on an initial enrollment survey.

The discussion forum in the Orientation unit of each course was an introductory forum that asked participants to introduce themselves and state why they are enrolled in the course. Prior research used topic modeling methods of these discussion forums to identify four themes for motivation among the same participants of this study (Chapter 4; Barker, 2021). Of the participants that accessed at least Unit 1 of any of the courses, it was found that 946 posted in this forum about their reasons for initially enrolling in the course(s). Four themes for motivation were identified, see Table 13. Those 946 participants who participated in the introductory discussion forum were assigned one of these four topics. From now on these will be referred to as *self-stated goals*, since these were goals determined from statements participants made.

Table 13
Self-stated goals determined by themes for motivation identified in topic modeling study

Self-stated goal	Theme for Motivation	Description These participants are motivated by….
1	Course specific goals	...goals that are listed specifically in the description of the courses.
2	Continuing Professional Learning	...continuing their general professional practice, including earning CEUs, taking the course as a requirement, or taking/retaking a course after being previously enrolled.
3	Pedagogical goals	...learning materials in the course that will make their classes more engaging, preparing to teach statistics in an upcoming course, or increase their general pedagogical skills.
4	Learn Statistics/ Increase Confidence	...either learning statistics or increasing their confidence to teach statistics.

A second source of data to identify motivation of participants was the enrollment survey that participants completed upon enrollment in a course (see Appendix A and B). Across all courses, one question asked on this survey was "Which of the following best describes your primary reason for enrolling in this course?". There were thirteen possible choices a participant could choose, see Table 14. Earlier course offerings let participants choose their top three reasons for enrolling, later offerings only asked the participants to provide one reason for enrolling (

Table **14**). Because of this, some participants only have one goal, some have three. These goals will now be referred to as *closed-ended goals*, since these goals are chosen from a closed-ended list.

Table 14

Closed-ended goals chosen by participants as primary reasons for enrolling in a course on enrollment survey

Goal	Reason for enrolling
1	Strengthen my understanding of how to engage students in statistical investigations
2	Improve my ability to use rich data sources to support investigations
3	Improve my ability to use dynamic tools to visualize and analyze data
4	Just browsing
5	Deepen my knowledge of the course topic(s)
6	Connect with peers/colleagues/ Exchange ideas and experiences with other educators
7	Collect resources and tools for my practice/Collect new resources or tools
8	Earn a certificate of accomplishment/renewal credits/Earn a certificate of completion
9	Collaborate on joint projects
10	Engage in fun and inspiring activities
11	Deepen my understanding of how students reason with data
12	Make changes to my professional practice
13	Experience learning in a MOOC-Ed

A binary matrix was created using these two sources of motivation, self-stated goals and closed-ended goals. This motivation matrix consisted of 1,949 rows that represented each participant, and 43 columns. Four of the columns indicated which self-stated goal from Table 13 was assigned to a participant (if any) who had posted in the introductory forum. Each of the 13 closed-ended goals were assigned a column to indicate if it was chosen as goal 1, goal 2 or goal 3. For instance, the column goal1_4 showed the first closed-ended goal chosen was the fourth closed-ended goal listed in Table 14. Thirteen columns for three possible closed-ended goals resulted in 39 columns. For each participant, they were assigned 0s or 1s; a 0 represented that a participant did not have a particular goal and 1 represented that a participant had chosen a closed-ended goal (Table 14) or had been assigned to a specific self-stated goal (Table 13).

Figure 11 shows a truncated view of the motivation matrix that has a total of 39 columns. The following describes how the motivation of two participants can be described with this matrix. Participant 526_9 was not assigned a self-stated goal (they did not participate in the introductory discussion forum) and chose the first goal in

Table **14** as their first closed-ended goal. Participant 728_58 was assigned self-stated goal 1 (see Table 13) and chose closed-ended goal 6 as their first reason for enrolling.

Figure 11

First rows of motivation matrix created with self-stated (stated) and closed-ended goals (ce goal).

Userid Bycourse	stated goal1	stated goal2	stated goal3	stated goal4	ce goal1_1	ce goal1_2	ce goal1_3	ce goal1_6	ce goal1_8	ce goal1_11
526_9	0	0	0	0	1	0	0	0	0	0
526_58	0	0	0	0	0	0	0	0	0	0
583_40	0	1	0	0	1	0	0	0	0	0
696_40	0	1	0	0	0	1	0	0	0	0
728_58	1	0	0	0	0	0	0	1	0	0
771_40	0	1	0	0	1	0	0	0	0	0
804_9	0	0	0	0	1	0	0	0	0	0
886_9	0	0	0	0	0	0	0	0	1	0
886_73	0	0	0	0	0	0	0	1	0	0
886_76	0	0	0	0	0	0	0	1	0	0
954_9	1	0	0	0	0	0	0	0	0	1
972_40	0	0	0	0	0	1	0	0	0	0
1163_52	0	0	1	0	1	0	0	0	0	0
1163_76	0	0	0	1	0	0	0	1	0	0
1168_40	1	0	0	0	0	0	0	0	0	0
1211_40	0	0	0	0	0	0	0	0	0	0

Engagement Data

The click-log data that was collected as participants engaged in the course was organized to create an engagement matrix like the motivation matrix described above. Click-log data collected includes a timestamp and description of every instance that a participant clicked on any part of the course, referred to as a *hit*. This data was broken down for each participant by number of hits per course, unit, week, discussion forum, and page type. See Appendix K – Variables Used for Cluster Analysis for a description of the data collected. This resulted in 83 variables that were used in the engagement matrix for each participant.

A subset of the engagement matrix is shown in Figure 12. The first row shows that participant 526_9 opened a course module a total of 57 times and a discussion forum 42 times, though they only posted to a forum once. Participant 696_40 opened a course module (or unit) 63 times, visited a discussion forum 24 times, posted twice, attempted a question twice, viewed a resource page 18 times, and clicked on a video 106 times. There are other fields in this row that are not pictured, this list can be found in Appendix K.

Figure 12

Subset of engagement matrix created from click-log data.

Userid Bycourse	course_module	discussion	post	question	resource	video
526_9	57	42	1		1	
526_58	2					
583_40	12	1			2	8
696_40	63	24	2	2	18	106
728_58	17	3			6	5
771_40	51	19	5	12	21	45
804_9	52	2		5	54	1
886_9	16	7			5	5
886_73	1					
886_76	1	2				
954_9	119	57	7	19	23	66
972_40	4				1	4

Cluster analysis using k-means clustering

Cluster analysis divides a set of data into groups or clusters that are similar based on predetermined algorithms. Since the goal of cluster analysis is to determine how similar individuals are, the matrices like those described above are used to determine a distance index between participants. Different methods of cluster analysis use different ways to determine the distance between participants (Battaglia et al., 2016). This study used K-means clustering to determine the clusters. K-means clustering divides observations into groups by randomly assigning *k* observations to be the center of a group (James et al., 2013). Then the remaining observations are assigned to those *k* groups so that the within-cluster variation between assignments is minimized. The *kmeans* function in R was used to determine the clusters. This function allows the user to determine how many times the algorithm is performed, each time randomly choosing different centers of each cluster to minimize the within-cluster variation (James et al., 2013). Higher number of centers were chosen until the within-cluster variation was no longer decreasing.

To determine the ideal number of *k* clusters, the *NbClust* function in the *NbClust* package was used (Charrard, et al., 2014). This function calculates 30 different indices that have been previously created to determine the ideal number of clusters. The function uses the majority rule to determine the ideal number of clusters; the ideal number that is chosen by the most indices should be the number of *k* clusters assigned (Charrard, et al., 2014). See Appendix J - R code for Motivation and Engagement Cluster Analysis for the R code used to create the clusters. The clusters were then analyzed to determine common features among motivation and engagement.

Results

Results of the cluster analysis are shared in three parts. The first section gives an overview of the clusters identified based on motivations for taking the course. The second section describes the clusters found by using the engagement data of the participants. Then the final section determines if there is a relationship between motivation and engagement clusters.

What motivates participants to enroll in online professional development courses for statistics educators?

The possible goals that were chosen by each participant on the enrollment survey are shown in

Table **15**. There were 13 possible goals to choose from, with some participants choosing just one, and some choosing their top three, depending on which enrollment survey they took. One of the goals were not chosen by any of the participants (Goal 12: Make changes to my professional practice). Goals 1, 2 and 3 were not on the enrollment survey for those enrolled in TSIR. After the clusters were determined these goals were then categorized into one of four broader goals: goals directly linked to the course objectives, just browsing, earn a certificate of completion, or goals generic to MOOC-Eds.

The *NbClust* function determined that 3 clusters were the optimal number of clusters for the motivation matrix described previously. The *kmeans* function was used to cluster all participants into one of 3 clusters. Participants were assigned to 3 clusters as follows: cluster 1 – 954 participants, cluster 2 – 631 participants, and cluster 3 – 364 participants.

Table 15
Choices on enrollment survey organized by broad goals. Note the numbering of the goals only has to do with how they were ordered on the enrollment survey.

Broad Goal	Closed-ended goal	Reason for enrolling
Goals directly linked to course objectives	1	Strengthen my understanding of how to engage students in statistical investigations
	2	Improve my ability to use rich data sources to support investigations
	3	Improve my ability to use dynamic tools to visualize and analyze data
	5	Deepen my knowledge of the course topic(s)
	6	Connect with peers/colleagues/ Exchange ideas and experiences with other educators
	7	Collect resources and tools for my practice/Collect new resources or tools
	11	Deepen my understanding of how students reason with data
Just browsing	4	Just browsing

Table 15 (continued)

Earn a certificate of completion	8	Earn a certificate of accomplishment/renewal credits/Earn a certificate of completion
Goals generic to MOOC-Eds	9	Collaborate on joint projects
	10	Engage in fun and inspiring activities
	12*	Make changes to my professional practice
	13	Experience learning in a MOOC-Ed

*goal not chosen by any of the participants

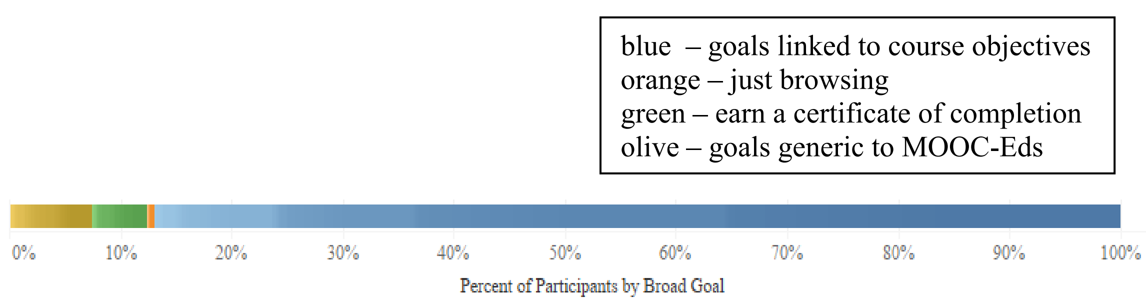
Figure ***13*** shows the percentage of broad goals chosen by the participants overall, then by each cluster.

Figure ***13*** shows how participants chose their goals for enrollment combined with their topic modeling goals in varying shades of color. The color of each bar indicates the first goal chosen on the enrollment survey. The shading indicates how the second and third choice were made as well as what topic modeling goal was assigned. For example, on the far-right end of the blue bar, with the darkest shade of blue, are those people who had chosen goal 1 as their only goal and were not assigned a topic modeling goal. On the left end of the bar, in the light blue, are those that chose goal 1 first with two other goals and a topic modeling goal.

Figure ***13*** shows that most people chose broad closed-end goals specific to the course objectives. There are some differences when looking across the clusters. Motivation cluster 1 has the highest percentage of participants whose first goal was earning a certificate of completion (10%) where cluster 2 and 3 had no participants who chose this as their first closed-ended goal. Motivation cluster 1 is also the only cluster with participants that chose just browsing as their first closed-ended goal (1.5%). Motivation cluster 1 also has the only group who chose closed-ended goals that are generic to MOOC-Eds as their first closed-ended goal (~15%). Cluster 2 and 3 first closed-ended goals were only goals linked to course objectives. When this graph is broken down by self-stated goals, there are no clear patterns of differences between the three clusters (see Figure 14).

Figure 13

Top graph, percentage of all participants who chose each broad closed-ended goal. Bottom graph, percentage of each cluster that chose each broad closed-ended goal.



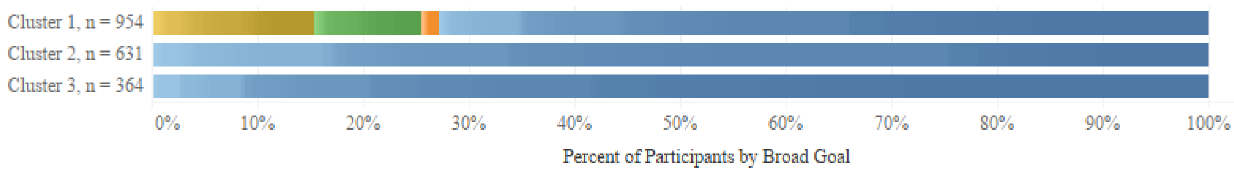


Figure 14

Proportion of each cluster assigned self-stated goals described in Table 13. Green indicates no goal assigned, participant did not participate in discussion forum

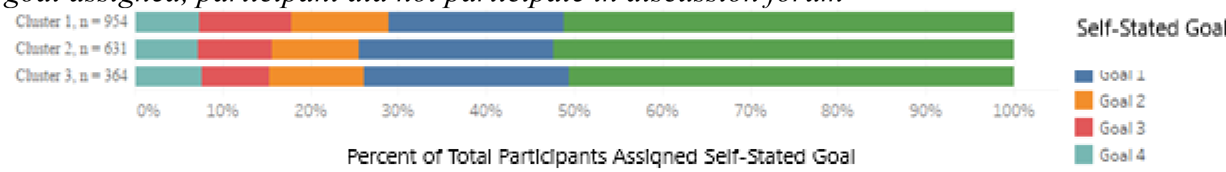


Figure 15

Top graph, percentage of all participants that chose each closed-ended goal. Bottom graph, percentage of participants that chose each closed-ended goal by cluster.
Each color represents the first closed-ended goal chosen as indicated in

Table **14**. *From right to left: ce goal 1 – light purple, ce goal 2 – dark purple, ce goal 3 – brown, ce goal 4 – orange, ce goal 5 – green, ce goal 6 – olive, ce goal 7 – teal, ce goal 8 – red, ce goal 9 – grey, ce goal 10 – black, ce goal 13 – purple.*

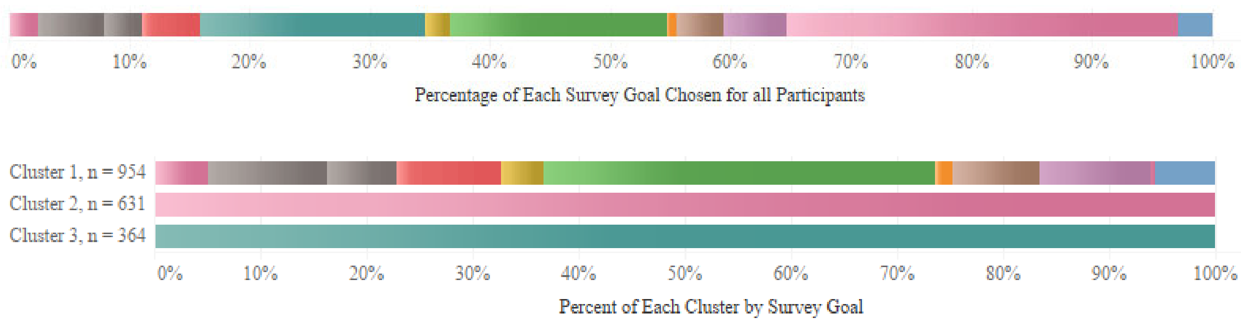


Figure *15* further breaks down the clusters by the 12 closed-ended goals participants chose from the enrollment survey. Like

Figure ***13***, the shading of each color indicates the second and third enrollment survey choices and self-stated goals of participants.

Cluster 1, 2 and 3 had a mixture of participants who enrolled in TSDI and TSIR, whereas Cluster 2 was entirely comprised of TSDI participants. Cluster 1 participants had a combination of all closed-ended goals as their first goal, except for closed-ended goal 1. Cluster 2 participants all chose closed-ended goal 1 (Strengthen my understanding of how to engage students in statistical investigations) as their first goal. This closed-ended goal was not available for those enrolled in TSIR, thus this group is the only one that contained only participants who took TSDI. Cluster 3 participants all chose closed-ended goal 8 (Collect resources and tools for my practice/Collect new resources or tools) as their first goal.

To classify the clusters, the information presented above was used to create a general categorical description to describe *most* of the participants in each cluster (see

Table **16**). There are variants in each cluster that may not fall under the description, but this is a best effort to classify the clusters. Cluster 1 participants were a mix of participants from both courses, with most enrolled in TSDI (70%) and 30% in TSIR. Though most participants chose closed-ended goals specific to course goals, this was the only group that also had participants whose closed-ended goals fell under the other 3 broad categories outlined in Table 15. The closed-ended goal chosen most often was goal 5 (Deepen my knowledge of the course topics). Cluster 1 will now be referred to as *Professional Learners for Teaching Statistics.* Cluster 2 was made up entirely of participants enrolled in TSDI. Their closed-ended goals were specific to that course, goals supporting students through data investigations. They will be referred to as *Statistics Investigators.* Cluster 3 participants were enrolled in both courses, TSDI (48%) and TSIR (52%). They are referred to as the *Teaching Resource Collectors*. Their main goal was to collect new resources and tools for their practice.

Table 16

Motivation categories for participants enrolling in OPD courses

Cluster Number	Cluster Name	Number of Participants in each Cluster	Description
1	Professional Learners for Teaching Statistics	954	These participants were mostly TSDI participants, with 30% in TSIR. Most of the goals chosen were specific to the course goals, but they were the only group who chose primary goals deepening knowledge of course topics.
2	Statistics Investigators	631	These participants were entirely comprised of TSDI participants. They all chose as their primary goal to strengthen their understanding of how to engage students in statistical investigations.
3	Teaching Resource Collectors	364	These participants were almost equally split between TSDI and TSIR participants. The participants were mainly interested in collecting tools and resources for their practice.

How do participants of OPD for statistics educators engage in the course?

Recall that the engagement matrix used for the cluster analysis of the participants of this course contained 83 variables. The *Nbclust* function determined that either 2 or 3 clusters were the ideal number of clusters to partition this data. The *kmeans* function was used to assign each participant to one of three clusters. There was a large variation of the number of participants in each cluster (see

Table 17).

Unlike the motivation clusters that only had participants of TSIR in the third cluster, this engagement cluster analysis had participants in TSDI and TSIR in all three clusters, though the number of participants for TSIR was very small compared to TSDI, mainly since TSDI was offered 7 times compared to TSIR only offered 3 times.

Table 17 shows the breakdown of participants in each engagement cluster by course.

Table 17

Count and percentage of participants in each engagement cluster that are enrolled in TSDI or TSIR

Cluster	1 Count (%)	2 Count (%)	3 Count (%)
TSDI	73 (93.6)	312 (84.8)	1,263 (84.0)
TSIR	5 (6.4)	56 (15.2)	240 (16.0)
Total	78	368	1,503

The engagement clusters were then analyzed to identify any differences across all the possible variables. The results here will focus on comparisons across clusters of click-data over time, the units opened, the resources used in the courses, and engagement in discussion forums.

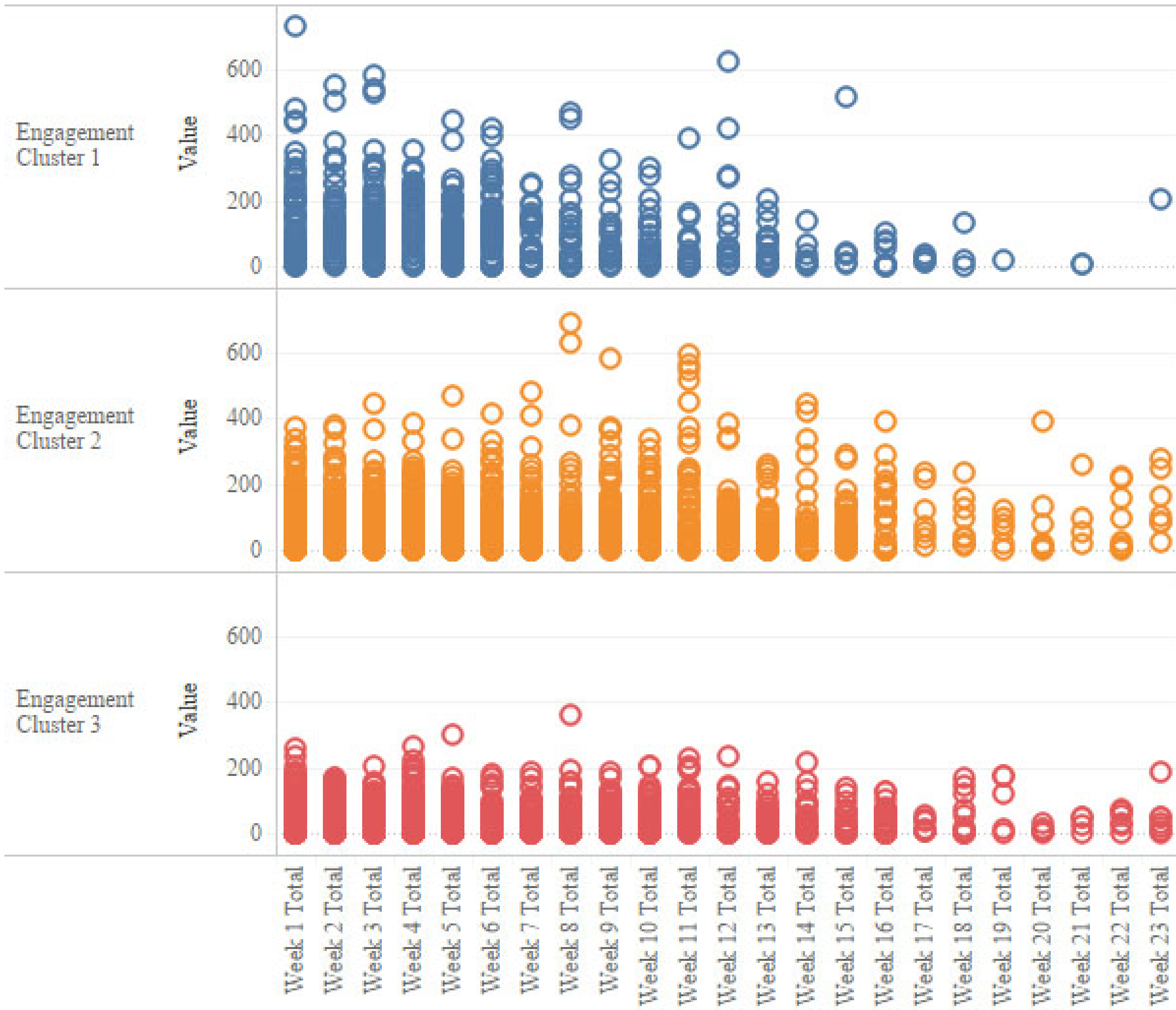
The number of weeks that each of the 10 courses were open varied from 6 weeks to 23 weeks. All courses had 6 units (an orientation unit followed by 5 units of course material). The course instructor would send out an announcement to enrolled participants roughly at the beginning of the week for the first 6 weeks to introduce each unit. This generally bought more participants back into the courses in the first 6 weeks than the other weeks. Figure 16 shows the number of hits for each participant separated into the three engagement clusters. Each dot represents a participant's participation in each week. Here we can see that though Engagement Cluster 1 has significantly fewer participants than Engagement Cluster 2 or 3, they clicked on the course much more often.

Engagement Cluster 1 has a much wider confidence interval than Engagement Clusters 2 or 3, indicating that they have much higher variation in the weekly hits. This can also be seen when referring to the number of individual hits that are shown in Figure 16.

Figure 17 shows the average number of hits for each engagement cluster for weeks 1 through 13. This average was determined by dividing the total amount of hits for the week for each cluster by the total number of participants of each cluster who *engaged in that week*, not simply by the total number of participants in each cluster. For instance, in Week 1, outliers were used to calculate averages (those that click at a higher rate than anyone else in a cluster). In Figure 16, outliers can be seen for each week. Since a participant could have had a high engagement for one week and not another, it did not make sense to remove them because engagement can change over time.

Figure 16

Weekly number of hits by each participant for weeks 1 through 23 broken down by engagement cluster.

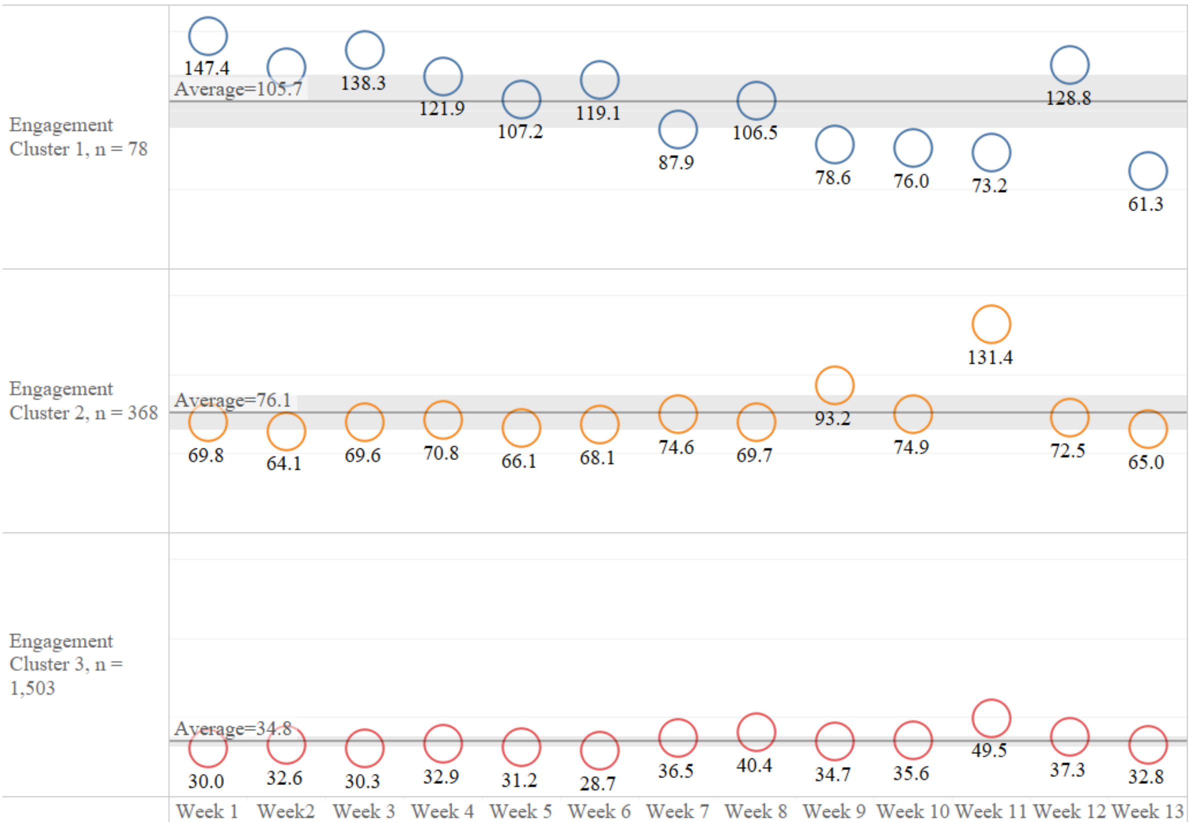


When comparing the average number of hits through the weeks, Engagement Cluster 1 had a higher average number of hits than the other 3 (see Figure 17). The average number of hits was calculated by adding the total hits per cluster for a week and dividing by the number of participants that engaged in that week. For instance, in Week 1 there were 60 active participants from Engagement Cluster 1 who totaled 8,842 hits, for an average of 147.4 hits. Engagement Cluster 1 has a much wider confidence interval than Engagement Clusters 2 or 3, indicating that they have much higher variation in the weekly hits. This can also be seen when referring to the number of individual hits that are shown in Figure 16.

Figure 17 shows the overall weekly average per cluster by a line through each cluster's averages, as well as a 95% confidence interval in the shaded grey area surrounding the average line. Engagement Cluster 1 averaged over 105 hits per week per participant the first 6 weeks, which is higher than any of the averages in the other clusters. Engagement Cluster 2 averaged between 69.8 and 70.8 hits the first six weeks, then dropped off after that. Engagement Cluster 3 never averaged over 50 hits per week. All three clusters show a sharp rise in hits in Week 11 or 12, which is likely due to participants trying to finish course requirements in the last weeks. The confidence interval surrounding each cluster's averages also shows that there is much more variation in the amount of hits in Cluster 1 than the other clusters. Engagement Cluster 1 has a much wider confidence interval than Engagement Clusters 2 or 3, indicating that they have much higher variation in the weekly hits. This can also be seen when referring to the number of individual hits that are shown in Figure 16.

Figure 17

Weekly average number of hits by participants in each cluster for weeks 1 through 13. The average is determined by the total number of hits for the week divided by the total number of participants that engaged in that week. There is an average line for each cluster, with a 95% confidence interval surrounding that line in grey in an attempt to quantify the variation.

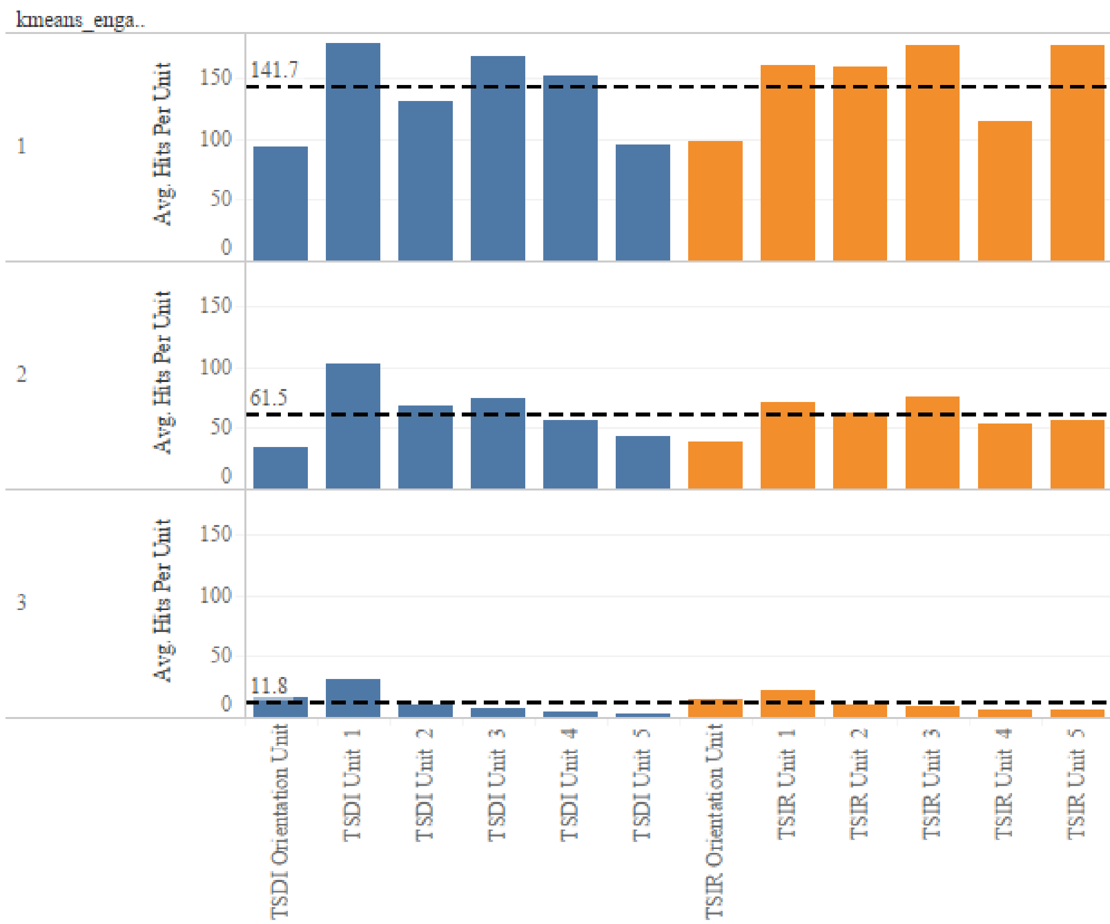


The average number of hits in each unit was then compared across engagement clusters. Figure 18 shows the total number of hits per participants in each cluster for a unit divided by the number of participants in each cluster that visited a unit. For instance, in Engagement Cluster 1 the five participants that participated in TSIR all eventually clicked in TSIR Unit 5, for a total of 880 hits, thus the average number of hits for that cluster is 176. The dashed line in each cluster shows the average number of hits across all units in each cluster. Across all 3 clusters the highest average hits occur in Unit 1 and are typically lowest in Unit 5. The only exception to this is

Engagement Cluster 1 which has a higher average in Unit 5 of TSIR than any of the other units in TSIR. The average unit hits in Engagement Cluster 1 are high across both courses. The unit hits in Engagement Cluster 2 are close to the average, which is much lower than the average in cluster 1. Engagement Cluster 3 hits a peak in TSDI Unit 1 at 31.3 hits then drastically drop off after unit 1 across both courses.

Figure 18

Average number of hits in each unit per participant in each engagement cluster. The blue bars represent units in TSDI, the orange bars represent units in TSIR. The dotted line is the average number of hits per unit for each cluster.



When looking at what participants in each of the engagement clusters are clicking on when they visit the courses, there are not very distinct differences. **Error! Not a valid**

bookmark self-reference. shows the average number of hits of types of pages that are clicked on when participants in each engagement cluster visit the courses (see Appendix K – Variables Used for Cluster Analysis for a description of all page types). Engagement Cluster 2 opened a course module on average slightly higher than Engagement Cluster 1. The hits for course module indicate the number of times the participant opened a new page in a module. This number is high across engagement clusters since most pages were designated as module pages to open other resources. The average number of hits for discussion pages and videos were similar for Engagement Cluster 1 and 2. Engagement Cluster 2 clicked on the course module completion page at a slightly higher average than Engagement Cluster 1, implying that they reached the end of units (or modules) more often. Across all 3 engagement clusters, participants tended to visit discussions slightly more than viewing videos.

Table 18
Average number of hits of page type by participants in each engagement cluster. See Appendix K for a description of each of these types of pages.

Engagement Cluster	Course Module	Opened a Discussion Forum	Viewed Video	Completed Course Module	Opened Resource Page
1	53.26	37.18	33.79	16.44	14.29
2	55.64	34.48	31.78	20.86	13.10
3	25.37	15.72	14.19	9.08	7.79

The final comparison will look at how often the participants in each engagement cluster visited discussion forums and how often they posted in the forums. Table 19 shows the total number of times all participants in each engagement cluster viewed a discussion forum, posted in a forum, how many times the post was a reply and how many times the post was the start of a new discussion thread. All the engagement clusters viewed discussion forums more than they posted, which implies that participants were reading a lot of posts. All the participants in

Engagement Cluster 1 posted at least once, all but two participants in Engagement Cluster 2 posted at least once, but 456 participants (30%) in Engagement Cluster 3 never posted in a discussion forum.

Engagement Cluster 2 had the highest number of posts overall, with 3,747 total posts across all courses. Engagement Cluster 1 had the highest average number of posts, with 17 posts per participant compared to Engagement Cluster 2 that had 10 posts per participant. Engagement Cluster 3 only averaged two posts per participant. Of the total discussion forum posts, Engagement Cluster 1 and 2 started a new discussion thread about 30% of the time (5/17 for cluster 1, 3/10 for cluster 2). Participants in Engagement Cluster 3 were equally likely to have started a thread as responded to one on average (1/2 for both).

Table 19

Count and averages of the number of times participants viewed a discussion forum, posted in a forum, replied to a previous thread, or started a new thread.

Engagement Cluster	**Number of participants who posted at least once**	**Discussion Forum Views**	**Discussion Forum Posts**	**Replies to a previous discussion thread**	**Starts of a new discussion thread**
	Total (% of cluster)	Total (Average)	Total (Average)	Total (Average)	Total (Average)
1	78 (100)	17,723 (227)	1,417 (17)	970 (12)	357 (5)
2	366 (99)	26,584 (72)	3,747 (10)	2,464 (7)	1,193 (3)
3	1,047 (70)	17,588 (12)	2,414 (2)	1,277 (1)	1,056 (1)

Table 20 outlines how many people in each engagement cluster made it to Unit 5 and how many accessed a certificate of completion. To open each unit, participants had to access the first page of the unit. Participants could access each unit in any order they wanted. In prior research of TSDI and TSIR participants, accessing Unit 5 has been used as a benchmark for "completing the course" (Mojica et al., 2018). This table also includes those that earned a certificate of completion, which is recorded when a participant opens the certificate of completion page. This page was only accessible if all requirements had been met for the certificate. This benchmark is kept for this study since earning a certificate of completion was a specific goal set forth by some participants. Engagement Cluster 1 and 2 have similar rates of participants who accessed Unit 5 or earned a certificate of completion. Engagement Cluster 3 had about 34% people access Unit 5 but not actually earn a certificate of completion (though they may have earned it, but never accessed the page).

Table 20
Count and percent of participants in each engagement cluster who accessed unit 5 and earned a certificate of completion

Engagement Cluster	**Accessed Unit 5**	**Earned a certificate of completion**
	Total (% of cluster)	Total (% of cluster)
1	75 (96.2)	64 (82.1)
2	304 (82.6)	221 (60.1)
3	252 (38.2)	65 (4.3)

Like the motivation clusters, the information presented here was used to form a *general* description of the engagement clusters created using the engagement data matrix (see

Table 21). These descriptions are meant to give an overall view of the behaviors of the participants in the engagement clusters and will not likely describe every person in the cluster.

The three engagement clusters are highly active course completers, consistent course completers, and least active course fizzlers.

Table 21
Name and description of engagement clusters

Engagement Cluster	Cluster Name	Number of Participants in each Cluster	Description
1	Highly active course completers (HACC)	78	This small cluster of individuals were much more active than the other clusters. They tended to visit pages more often in any given week, across all units of the courses they were enrolled in and posted often in forums. They had high rates of completing the course, whether that be in accessing the final unit or earning a certificate of completion.
2	Consistent course completers (CCC)	368	These participants are consistent in how they participate in the course through time and throughout the units. They tend to post in forums consistently and participate in all units at about the same rate. This leads to most participants making it to Unit 5 or earning a certificate of completion.
3	Least active course fizzlers (LACF)	1503	The participants in this cluster tend to fizzle out after Unit 1 of the courses. They seem to come to visit the course at the beginning, and even post in the first forums, and then do not return to complete more units.

How is motivation for enrolling in OPD for statistics educators related to how participants engage in the course(s)?

So far, the results of this study have determined three ways to group participants based on what motivated them to join a course(s) and three ways to group participants based on how they engaged in the course they were enrolled in. The next step was to determine if there is any relationship between what motivates people to take a course and how they engaged in the course. Table 22 shows how many participants are in each combination of the six different possible clusters.

Table 22 shows that within the highly active course completers (HACC) 82% of participants were classified as *Professional learners for teaching statistics* or *Statistics investigators*. This indicates that most of their goals were aligned to the goals of TSDI. Though there were highly active course completers who were enrolled in TSIR, about 94% of them were enrolled in TSDI. Approximately 53% of the consistent course completers (CCC) were classified as *Professional learners for teaching statistics*, as well as 49% of the least active course fizzlers (LACF).

Table 22
Number and percentage of participants in the six possible combinations of motivation and engagement clusters

Engagement Cluster		**Motivation Cluster**	
	Professional learners for teaching statistics	Statistics investigators	Teaching resource collectors
	Count (%)	Count (%)	Count(%)
Highly active course completers	29 (37.2)	35 (44.9)	14 (18.0)
Consistent course completers	196 (53.3)	106 (28.8)	66 (17.9)
Least active course fizzlers	729 (48.5)	490 (32.6)	284 (18.9)

There seems that there is very minimal relationship between motivation and engagement Table 23. Looking across the *Professional learners for teaching statistics*, 3% were HACC, 20.6% were CCC and 76.4% were LACF. The numbers for HACC and CCC are only a little different for *Statistics investigators,* 5.6%, 16.8% and 77.7% respectively. The *Teaching resource collectors* had 3.9% HACC, 18.1% CCC, and 78.0% LACF. The percentage of LACF is almost identical across clusters. Though the *professional learners for teaching statistics* had more HACC, this comparison seems nominal to say those motivations lead to higher engagement. It is also interesting to note that the *professional learners for teaching statistics* had more people indicate that earning a certificate of completion was their primary closed-ended goal, and 20.4% of that motivation cluster did earn a certificate compared to 15.1-15.8% of the other motivation clusters.

Table 23
Count and percent of each motivation cluster by engagement cluster

Motivation Cluster	**Engagement Cluster** Highly Active Course Completers Count (%)	Consistent Course Completers Count (%)	Least Active Course Fizzlers Count (%)
Professional learners for teaching statistics	29 (3.0)	196 (20.6)	729 (76.4)
Statistics investigators	35 (5.6)	106 (16.8)	490 (77.7)
Teaching resource collectors	14 (3.9)	66 (18.1)	284 (78.0)

To further investigate any relationships between motivation and engagement, the participants were further broken down by the courses they were enrolled in. Recall there were 1,949 participants (identified by user id and course they enrolled in) and of those 636 had enrolled in more than one course. These 636 participants represent 280 unique individuals. The participants were then categorized by enrolling in TSDI only, TSDI plus TSIR, and TSIR only. These categories may have people that enrolled in the same course type twice. For instance, 143 participants enrolled in different sections of TSDI more than once, but never enrolled in TSIR (69 unique participants). There was a total of 479 participants (204 unique participants) who enrolled in at least one section of TSDI and TSIR, and only fourteen (7 unique participants) that had enrolled in more than one section of TSIR only.

There were 1,115 participants (by user id and course, not unique participants) who enrolled in TSDI and no other course (either just one time or multiple times).

Table **24** shows the count and percentage of these participants by motivation and engagement cluster. This shows no discernable difference between motivation types and engagement clusters among those enrolled in only TSDI. This is surprising since all the *professional learners for teaching statistics* were TSDI participants.

There were 479 participants (not unique participants) who enrolled in at least one offering of TSDI and at least one offering of TSIR. Though the number of participants classified as *professional learners for teaching statistics* is almost twice that of either *statistics investigators* or *teaching resource collectors*, there is a large difference in the percentages by engagement cluster (Table 25). A higher percentage of HACC tend to be *statistics investigators* (50%) compared to the *professional learners for teaching statistics* or *teaching resource collectors* (34.6% and 15.4% respectively). Additionally, a much higher percent of CCC tends to be *professional learners for teaching statistics* (61.1%) than the other motivation clusters. The percent of *teaching resource collectors* per engagement cluster is not higher than 26.2%. This result shows that those people who enrolled in both courses and are either *professional learners for teaching statistics* or *statistics investigators* tend to have higher levels of engagement and higher rates of course completion (defined as accessing Unit 5).

Table 24

Count and percent of each motivation cluster by engagement cluster for participants who only enrolled in a section(s) of TSDI. The percentages are calculated across the row.

Motivation Cluster	**Engagement Cluster** Highly Active Course Completers Count (%)	Consistent Course Completers Count (%)	Least Active Course Fizzlers Count (%)
Professional learners for teaching statistics, n = 535	17 (3.2)	107 (20.0)	411 (76.8)
Statistics investigators, n = 391	17 (4.4)	59 (15.1)	315 (80.6)
Teaching resource collectors, n = 189	9 (4.8)	44 (23.3)	136 (72.0)

Table 25

Count and percent of each motivation cluster by engagement cluster for participants who enrolled in at least one section of TSDI and TSIR

Motivation Cluster	**Engagement Cluster** Highly Active Course Completers Count (%)	Consistent Course Completers Count (%)	Least Active Course Fizzlers Count (%)
Professional learners for teaching statistics, n = 245	9 (34.6)	55 (61.1)	181 (49.9)
Statistics investigators, n = 118	13 (50.0)	18 (20.0)	87 (24.0)
Teaching resource collectors, n = 116	4 (15.4)	17 (18.9)	95 (26.2)

Discussion

There are many implications that could arise from this study. This section will first summarize the findings of this study. Then implications from the study for MOOC researchers will be shared followed by implications for those providing online professional development for statistics educators.

Wiebe et al. (2015) state that cluster analysis can be an effective way of analyzing the behaviors of participants within MOOCs by considering all their actions and not simply using descriptive statistics to describe actions. This study attempted to analyze the motivation and engagement of participants across 10 course offerings of 2 MOOC-Eds for statistics educators using cluster analysis. The participants of these courses were broken into three clusters to describe what motivated participants to initially enroll in the course, and three clusters to describe how they engaged in the course. Comparisons were then made across the combinations of motivation and engagement clusters to see if a relationship exists between motivation and engagement.

Though there could have been many clusters formed to describe motivation, ultimately three were determined, *professional learners for teaching statistics, statistics investigators,* and *teaching resource collectors*. *Statistics investigators* were ultimately only comprised of those that were enrolled in TSDI. *Professional learners for teaching statistics* and *teaching resource collectors* had a mixture of both. It seems obvious that those who enrolled in TSDI would choose goals focused on data investigations. But it is noteworthy that this happened through the cluster analysis process, which only used the motivation matrix (which includes goals chosen on a survey and the topic modeling goals, not which course they enrolled in) to cluster participants. What seems obvious to a human observer is not always obvious to a computer program

It is not surprising that of the 1,949 participants in this study 1,503 (77.1%) were least active course fizzlers. Prior research has shown that though MOOCs have many enrollees, those that complete a course are quite low (Kizilcec et al., 2020; Moore & Wang, 2021; Pursel, et al., 2016). For this study, 18.0% of participants earned a certificate of completion, whereas 45.4% accessed Unit 5. If we had defined completion rate as earning a certificate of completion, these participants are on par with most MOOCs, the average is around 20% (Kizilcec, et al, 2020). But not all participants wanted to earn a certificate of completion, there were many goals to choose from. When we look at just those who chose earning a certificate of completion as their primary goal (closed-ended goal 9) we see that 56.3% of those did earn a certificate (Figure 19). If we consider those that *accessed unit 5* as course completers, then those that chose goal 5 (deepen my understanding of course topics) perform the best (

Figure **20**).

Figure 19

Percentage of participants who earned a certificate of completion by goal. Goal 9 was "earn a certificate of completion". Blue indicates those that did not earn a certificate of completion, orange indicates those that did earn a certificate of completion.

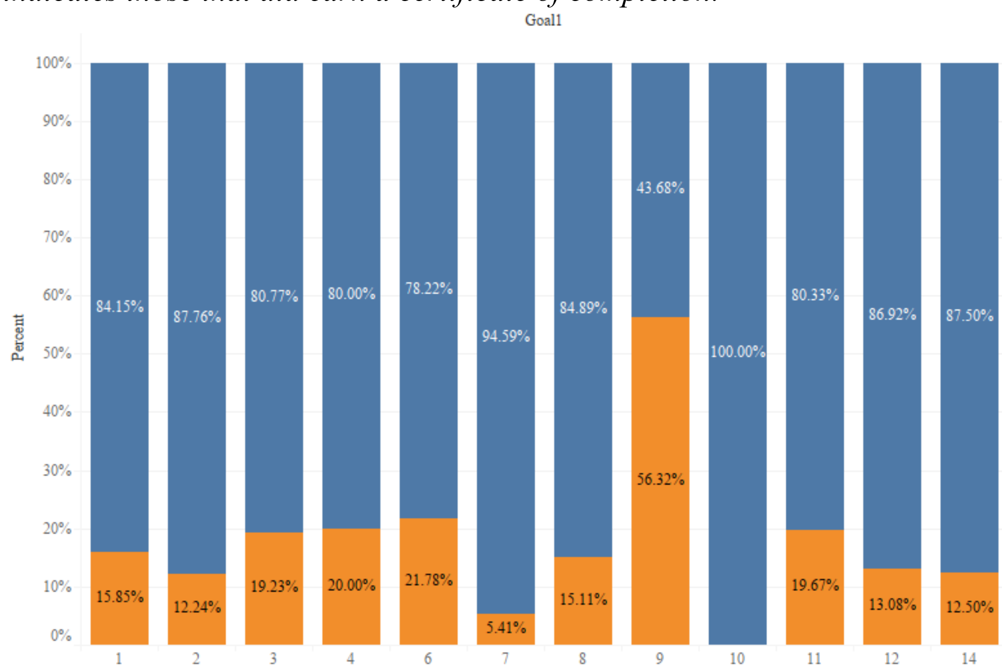
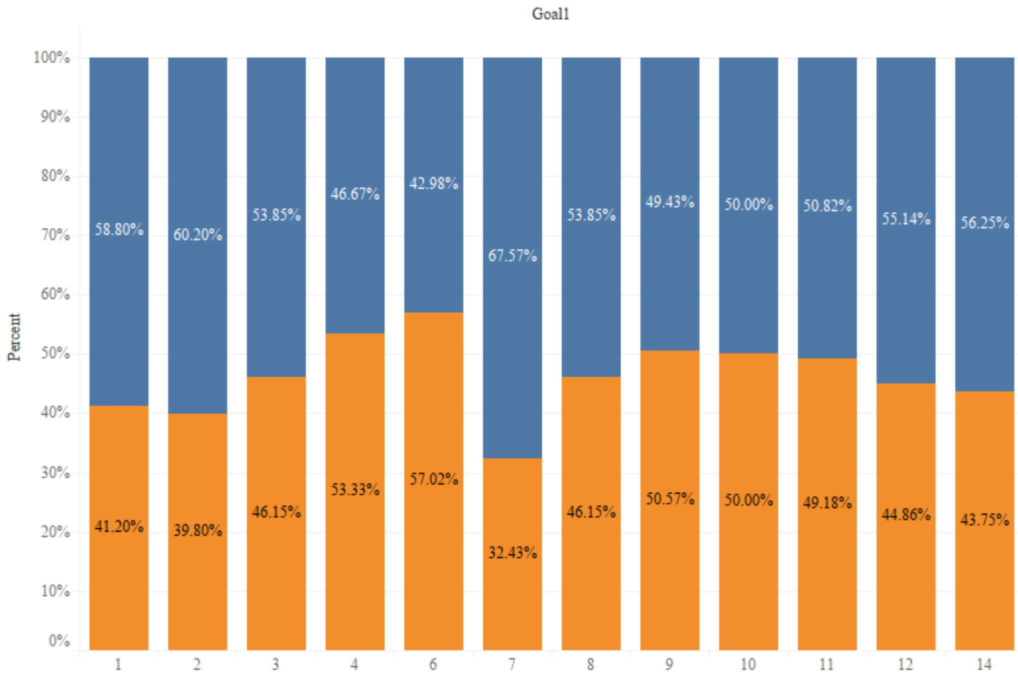


Figure 20

Percentage of participants who accessed Unit 5 by goal. Orange are those that reached Unit 5, blue are those that did not reach Unit 5.



Does motivation to enroll in a course affect how someone performs in a course? It certainly does. Participants of TSDI and TSIR who came to earn a certificate of completion usually did. And those that wanted to learn the course topics usually went through all the units. MOOC researchers should consider the motivation someone has when enrolling when measuring whether they completed the course. Measuring completion should focus on whether the participants met their learning goals.

The implication of this study for those offering professional development for statistics educators is that having courses with sustained duration, such as offering two successive courses, makes a difference in how people are engaged in the work. Darling-Hammond et al. (2017) identify seven characteristics of effective PD, one of which is *sustained duration*. Though what is considered a *good* amount of time is not defined, Darling-Hammond et al. (2017) insist that

PD that is "sustained, offering multiple opportunities for teachers to engage in learning around a single set of concepts or practices, has a greater chance of transforming teaching practices and student learning" (p. 15). In this study, those that had enrolled in TSDI and TSIR tended to be grouped into clusters with higher levels of activity. Additionally, 45.7% of those that enrolled in TSDI *and* TSIR accessed Unit 5 in both courses, with less of those enrolling in just TSDI or TSIR reaching Unit 5 in either course (31.6% and 31.8% respectively).

Limitations and Future Directions

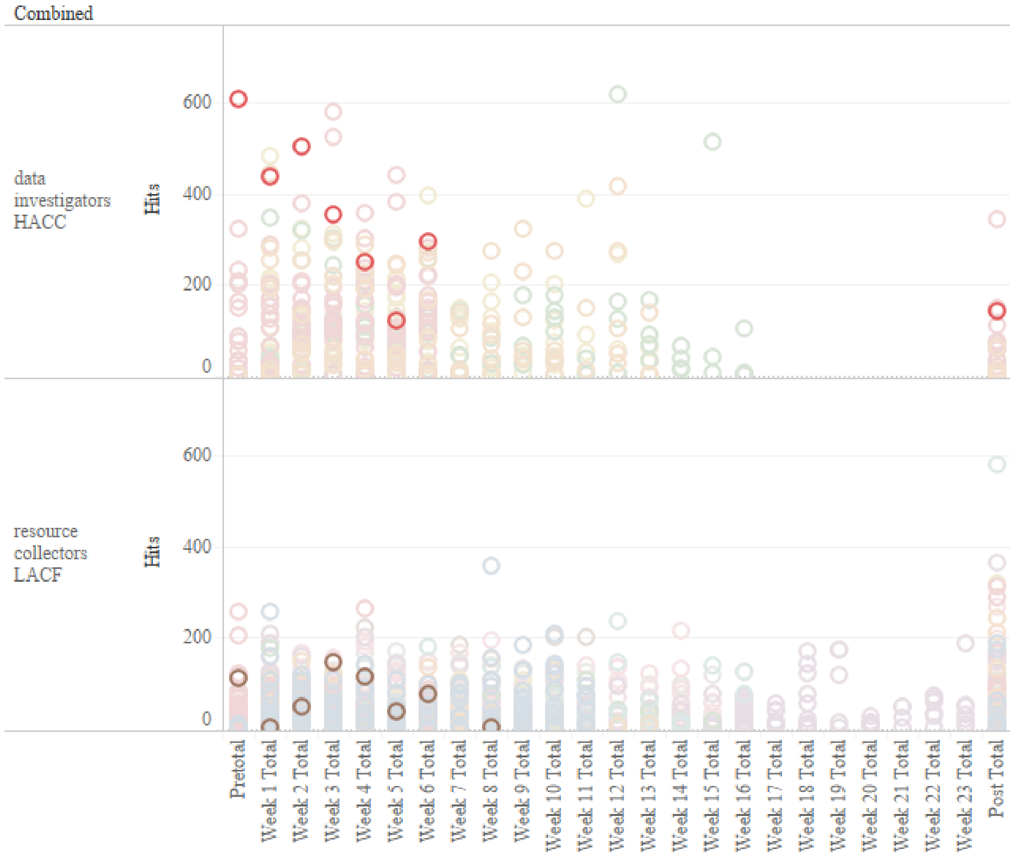
The results of this study should be considered with several limitations that existed in the analysis process. Unlike other studies of MOOC courses, the data for this study considered 10 courses that lasted for varying times. The length of these courses had to be normalized so that dates were not considered, and instead weeks were of consideration. This is important to mention since some courses may have been offered at times that were not as active, such as summer courses that lasted shorter times, or the one course that was open for 23 weeks, much longer than the others. Future studies may look at cluster analysis on just individual course offerings, then combine the findings.

Additionally, we were considering two successive courses instead of just one. Though this may have led to different interactions, it was interesting to see how cluster analysis did not include any participants of TSIR in one motivation cluster. Since only 3 of the 10 offerings were for TSIR, it was clearly underrepresented in the data. Additionally, TSIR and later course offerings of TSDI offered different choices for the enrollment survey (i.e., choosing one goal versus 3) which could have really skewed the outcomes of the cluster analysis.

Just as Wiebe et al. (2015) emphasized the importance of the individual, future studies could look more at individual participants instead of clusters. For instance, this study treated each time a participant enrolled in another course as a different individual. Because of this, individuals that enrolled in different courses can be tracked to see if their motivation or engagement changed. For instance, **Error! Not a valid bookmark self-reference.** shows participant 4513. This individual enrolled in a section of TSDI (top graph), then a couple of years later enrolled in TSIR (bottom graph). This graph shows that the person was very active in TSDI, often having over 200 hits per week, even coming back to the course later. This same person was not as active in TSIR (having much lower weekly hits), though they were clearly engaged throughout the first eight weeks. Their motivation changed from data investigator to resource collector because they chose different goals on the enrollment survey.

Figure 21

Participant 4513 engagement and motivation clusters in TSDI and TSIR



What happened to change this person from a highly active course completer to a least active course fizzler? Studying this and other individuals with similar patterns could help determine why a participant may engage highly in one course then not be as engaged in the next.

Conclusion

The goal of this study was like other studies that identified clusters of participants by motivation and engagement. MOOC participants have been grouped by intrinsic and extrinsic motivation (Moore & Wang, 2020; 2021; Wiebe & Sharek, 2016). We had hypothesized that the cluster analysis method would group the participants of TSDI and TSIR similarly, but instead participants were grouped by their closed-ended goals either being related to course objectives or not related to course objectives. Though extrinsic and intrinsic motivations are a clear way of defining motivation, we believe these two ways of grouping participants can also be useful for others analyzing participant motivation. The three engagement clusters we found (highly active course completers, consistent course completers, and least active course fizzlers) were like other clusters found in previous research based on levels of engagement (Thompson, et al., 2016; Frankowsky, et al., 2015). We did not find a clear link between the motivation and engagement clusters in this study, but it would be interesting to see if other researchers found any connection between goals chosen that are course specific and levels of engagement.

Kizilcec et al. (2020) posit a negative tone of the success of MOOCs as an alternative form of PD. Studying over 250,000 participants in 247 MOOCs, they found that even over 2.5 years of different interventions, completion rates still stayed low (~20%). For an individual considering something such as a MOOC-Ed to further their professional goals, these results would probably make most consider turning to another source. But this study, as well as others that consider motivation and engagement of educators, show that defining someone as successful as earning a certificate of completion cannot be the only way success is measured. For instance, 41.5% of those that had goals aligned to the course (*statistics investigators)* accessed all 5 units, and those that enrolled in both courses had 45.7% make it to the final unit. This is a more reassuring statistics to use to convince someone to join these courses.

It also cannot be overlooked, that when the data from this study is broken down by those that took both courses, the percentage of people who accessed Unit 5, and the percentage of people who were more active is higher. How often have people left a PD saying, “I wish I could continue learning about…"? These participants had that chance, and it seems to have paid off. Those who can create online PD for teachers of statistics should consider the possibility of offering successive courses, when possible, to fully engage teachers in statistical thinking.

CHAPTER 6 A STORY OF TWO MOOCS FOR STATISTICS TEACHERS: AN EXPLORATION OF MOTIVATION, ENGAGEMENT AND PROFESSIONAL GROWTH OF PARTICIPANTS

Journal

This chapter presents a journal ready article to be submitted to *JSDSE, Journal of Statistics and Data Science Education* an open access peer-reviewed journal published by the American Statistical Association. The journal disseminates knowledge for the improvement of statistics education at all levels from elementary to post-graduate as well as workplace education. Submissions are welcome from educators, practitioners, and researchers. Topics include but are not limited to innovation methods of instruction or assessment, research on teaching of statistics, use of computers in teaching, and distance education. This article will be submitted as an original research article. There are no guidelines for length, though they do state that authors should “avoid over-long papers”. Authors should submit a 200-page unstructured abstract as well as 3 to 6 keywords.

Abstract

Massive open online courses (MOOCs) that provide skills necessary to *do statistics* has become a popular alternative for on-the-job training, but there are less MOOCs available for educators who may need professional development to *teach statistics*. This study explores the participants of two successive open online professional development courses for statistics educators. The first course introduced participants to using the statistical investigation cycle to aid students through data investigations and was offered a total of 7 times with a total of 3,115 enrolled participants. The second course focuses on pedagogy specific to inferential reasoning in the statistics classroom, offered 3 times for a total of 700 participants registered. This article shares the findings of a research study that investigated 1,592 active participants from both courses. Findings from a previous study on motivation and engagement are shared. A follow-up survey was sent to 1,592 participants to measure their professional growth after participating in the course(s). The survey included questions about the effect their participation had on their beliefs about teaching statistics, statistical knowledge, their current teaching practices, student outcomes, and influence on their professional community. Results from a small number of respondents (n = 50) gives evidence that the participants experienced positive professional growth because of their participation. These encouraging results provide evidence that more professional development opportunities such as these should be created to provide support for teachers of statistics.

Keywords: Statistics Education, Professional Development, MOOC, Online Learning, Professional Growth

Introduction

Massive Open Online Courses (MOOCs) have proven to be timely and convenient for extra on the job training (Christensen, et al., 2013). By 2021, there were many MOOCs available, specifically for skills that statisticians need. A search for the word *statistics* in Coursera's database, a leading MOOC host site, yields 2,225 courses covering statistics topics. But a quick search for *teaching statistics,* only yields 138 results, and of those none appear to be courses that may help someone who is interested in becoming a better statistics teacher (Coursera, n.d.). MOOCs are useful for people trying to *learn* statistics, but what about for people who want to learn to *teach* statistics? This article will explore the motivation, engagement, and professional growth of participants in two courses designed to help those who teach statistics.

Dr. Hollylynne Lee, a mathematics and statistics education professor at NC State University, has led two teams at the Friday Institute for Educational Innovation to design and implement two free successive MOOCs specifically for statistics education, *Teaching Statistics through Data Investigations* (TSDI) and *Teaching Statistics through Inferential Reasoning* (TSIR) (Hollebrands & Lee, 2020). TSDI was first offered in Fall 2015 for a total of 7 course offerings, the last offering in Fall 2018. TSIR was then released in Fall 2017 and was offered 3 times, the last offering in Fall 2019. The courses are archived at their host site, The Place: Professional Learning and Collaboration Environment along with a collection of other MOOCs for educators developed through the Friday Institute (https://place.fi.ncsu.edu/).

This article will give a brief introduction of the materials presented in the two courses, expand on some details of who took the courses, why they enrolled, and what they were doing when they took the courses. Preliminary findings from a 2021 survey taken by course participants to examine how participation affected their current teaching will be shared. It is our hope that this article offers some insight to other statistics educators to the value of offering professional development, such as this, to those that are not just interested in learning statistics, but also to those who are teaching statistics.

Background Literature

Increased effort to provide professional development (PD) opportunities for in-service teachers of statistics has been a result of the increased inclusion of statistics standards in the K-12 mathematics curriculum (Carver et al., 2016). Despite the increase of statistics standards in classrooms, pre-service mathematics teaches are often required to only take one statistics course in their teacher preparation program (Franklin, et al., 2015). Mathematical and statistical thinking are different (Cobb & Moore, 1997), and if pre-service teachers are not getting the preparation, they need to confidently teach statistics (Lovett & Lee, 2017), then there is a need for offering wide-scale professional learning opportunities for in-service teachers (Franklin et al., 2015). Though the need for PD specific to statistics education has been recognized, there are limitations of providing these sorts of opportunities at local levels (Franklin et al., 2015).

Recommendations for subject matter to include in PD to promote statistical thinking include developing a deep conceptual understanding of statistics instead of just performing statistical procedures (Franklin et al., 2005), actively engaging in the statistical investigation cycle (Franklin et al, 2015), and keeping educators current with technology for conducting statistical investigations (Biehler et al, 2013; Pratt et al., 2011). Increased conceptual understanding has resulted from PD opportunities that focus on specific statistical topics, such as measures of center and variation (Peters, et al.2014; Peters & Stokes-Levine, 2019). Teachers who have participated in PD where they engage in the statistics investigation cycle as a student would tend to better support their own students in statistics investigations (Makar & Fielding-Wells, 2011; McClain, 2009; Souza et al., 2015). Teachers have become empowered to use new technology in their own classrooms when participating in PD that uses technologies such as dynamic statistical software (Madden, 2014; Wassong & Biehler, 2014).

Providing these opportunities at the local level can be challenging. A statistics teacher may be the only one in a school or even a district that teaches statistics, making them feel isolated. Teachers are also often busy, having obligations outside of their classrooms. Online professional development (OPD) with similar goals to those described previously can be more convenient and timelier to those that do not have access to local seated PD. Though there have been blended online PD opportunities, where part of the experience is face to face and part is online (Akoğlu, 2018; Akoğlu, et al., 2019; Wassong & Biehler, 2014), there have been far fewer *fully online* PD experiences for teachers of statistics. OPD courses for in-service statistics teachers have been a source of increased statistical understanding and can provide a source of community among statistics educators (Garfield & Everson, 2009; Meletiou-Mavrotheris, 2011).

Fully online PD include MOOC-Eds (Massive Open Online Courses for Educators) that focus on statistics pedagogy (Lee & Stangl, 2015). Three such MOOCs have been developed. Dr. Stangl of Duke University and her team developed the *Teaching Statistical Thinking* MOOC. This MOOC began with an introduction of descriptive statistics, lessons on implementation of descriptive statistics in the classroom, followed by a focus on software that can be used for descriptive statistics (Lee & Stangl, 2015). Lee and her team created two MOOCs titled *Teaching Statistics through Data Investigations (TSDI)* and *Teaching Statistics through Inferential Reasoning (TSIR)*. Each course is meant to enhance teachers understanding of statistics and teaching strategies in middle school classes through introductory level college courses. TSDI and TSIR are the focus of this study. Details of TSDI and TSIR will be shared in the method section.

Research of MOOC participants have led many researchers to explore motivation for enrolling in a course as well as patterns of engagement while participating in the course (Frankowsky, et al., 2015; Perna, et al., 2014; Thompson, et al., 2016; Wilkowski, et al., 2014). Since MOOCs are meant to create individualized experiences to meet specific needs of participants, the reasons people come to a course or engage in a course will vary (Frankowsky, et al., 2015; Wiebe, et al., 2015). Identifying these factors can help course developers who plan to create similar PD opportunities.

Methods

Description of the Courses

TSDI and TSIR were both meant to attract participants interested in strengthening their statistics pedagogy from middle school to introductory statistics courses at the college-level. The goal of TSDI was to engage participants in thinking about teaching statistics in a way that was likely different from their current teaching practices. Participants in TSDI were introduced to the Students Approaches to Statistical Investigations (SASI) framework, which incorporates the four phases of the statistical investigation cycle (pose, collect, analyze, and interpret data), statistical habits of mind, and different levels of statistical sophistication (Franklin et al., 2015). TSIR was meant to be an extension of the materials in TSDI while emphasizing inferential reasoning. TSIR introduces participants to the Inferential Reasoning Task guidelines (Lee, 2017) as well as other resources and strategies to consider when incorporating inferential reasoning into their statistics courses.

Each course consisted of five units and an orientation unit (see

Table **26**). The courses were asynchronous with no live meetings. Each course was open for approximately 10-15 weeks. If participants completed the course requirements, they earned a certificate of completion that satisfied 20 hours of continuing education credits. Participants were encouraged to complete TSDI before taking TSIR, though it was not required.

Each unit consisted of approximately five sections of materials. The *Engage with Essentials* section included readings and videos that were created by the course design team or curated from open online resources. Another section included videos of the instructor and other experts in statistics education engaging in a discussion relevant to the subject of each unit, as well as videos or animations of students engaging in statistical investigations in classrooms. The *Investigate (TSDI)* and *Explore and Discuss (TSIR)* section gave participants an opportunity to explore a data set with technology tools as a student would, then discuss the experience with colleagues. Each course also had a *Discuss with your Colleagues* section that allowed open discussions among colleagues about what was learned in the unit. To earn a certificate of completion, participants had to access and engage with all materials in *Engage with Essentials,* complete all activities and engage in the discussion forum in the *Investigate (TSDI)* or *Explore and Discuss (TSIR)* section, and post at least once in the *Discuss with your Colleagues* forum for Units 1 – 5, as well as complete the end-of-course survey.

Table 26
Description of the units in both courses

Unit	TSDI	Description	TSIR	Description
0	**Orientation**	Meet lead instructor and overview of materials.	**Orientation and Review of SASI Framework**	Introduced to the course and colleagues and can review essential background material from TSDI.
1	**Considering the Possibilities of Teaching Statistics with Data**	Focus on what statistics is and why it is taught in schools. Explores possibilities of students engaging with real data and tools to engage with data.	**What is Inferential Reasoning?**	Learn core aspects of inferential reasoning, why it is important in statistics, and how it develops, from informal approaches with early learners to more formal approaches as learners get more sophisticated.
2	**Engaging in Statistics**	Examines differences between mathematics and statistics, learning the statistical investigation cycle, and considering habits of mind when working with data, and watching as a teacher engages students in a statistical investigation.	**Inferential Reasoning with Comparing Groups**	Deep dive into questions that provide opportunities for learners to compare two or more groups.
3	**Introducing Levels of Statistical Sophistication**	Explores a framework for supporting growth in students' statistical sophistication and digs deeper into statistical habits of mind. Introduced to a statistical task framework to design, adapt, and analyze instructional tasks and explore students' levels of statistical sophistication.	**Inferential Reasoning Between Samples and Population**	Generalizing from a sample to a population is often considered the quintessential way to make inferences in statistics.

Table 26. (continued)

Unit	TSDI	Description	TSIR	Description
4	**Delving Deeper into the Investigation Cycle**	Provides teaching and learning materials to assist in understanding the different components of a statistical investigation, including several resources that can be used in the classroom.	**Inferential Reasoning with Competing Models**	Focuses on how learners can engage with questions that focus on making decisions about which model is the most plausible for describing a population.
5	**Putting It All Together**	Considers how to change teaching practices that can really engage students in doing statistics with real data.	**Making Inferential Reasoning Essential in Your Practice**	Focus on making plans to change teaching practices that can really engage students in inferential reasoning. Reflect on, assess, and share what was learned throughout the course.

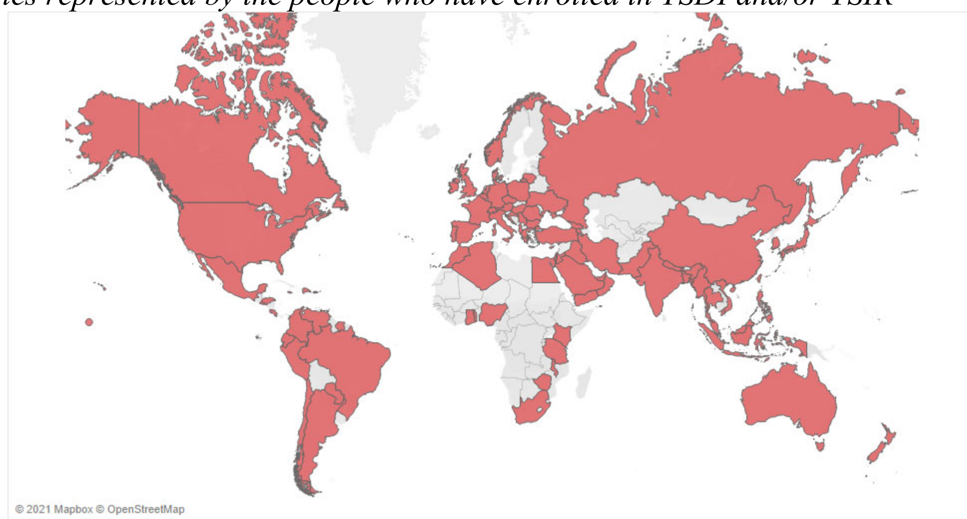
Course Participants

In the seven offerings of TSDI there were a total 3,115 people registered and in the three offerings of TSIR there were a total of 700 registered people. Of those registrants, 835 had registered for more than one course, leaving 3,106 unique participants across the 10 course offerings. Those who enrolled represent 94 countries, with the majority being from the United States. Enrollees represented all 50 states. Approximately 75% have a master's degree or higher and 61% identify as classroom teachers. There are other professions represented, such as researchers, professional development coordinators, and teacher educators.

As with most MOOCs, the number of people who enrolled in the course(s) is *much higher* than those that completed the course(s) (Erikkson, et al., 2017; Onah, et al., 2014). This is usually due to people enrolling just to see what the course has to offer (Hollebrands & Lee, 2020). To avoid analyzing the behaviors of these course *browsers,* we focus our attention on those that accessed at least Unit 1 of the courses. There were 1,592 participants who accessed at least Unit 1 in a course, with 357 of these participants registered for more than one course. For analysis purposes, each instance a person registers for a new course, we considered them a new participant. So, from now on when we refer to participants, there are 1,949 participants. Additionally, we identify course completion as accessing Unit 5, not just earning a certificate of completion.

Figure 22

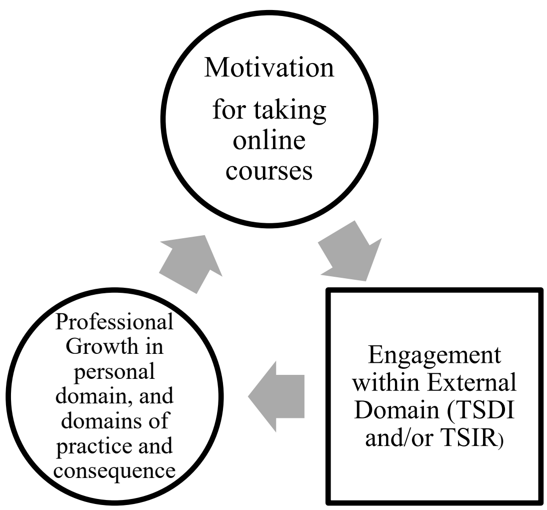
Countries represented by the people who have enrolled in TSDI and/or TSIR



A Framework for Motivation, Engagement and Professional Growth

The methods and results are framed around three aspects; motivation for taking a course (why did they enroll), engagement during the course (what did they do), and professional growth after taking a course (where are they now). The *Interconnected Model of Professional Growth (IMPG)* originally described by Clarke and Hollingsworth (2002) was adapted to frame our research. The IMPG model locates change for a person within four domains, external domain (sources of information, such as TSDI and TSIR), personal domain (knowledge, beliefs, and attitudes), domain of practice (professional experimentation, such as trying something new in a class), and domain of consequence (sustained changes and salient outcomes, such as consistently teaching about the statistics investigation cycle after being exposed to it in TSDI) (Clarke & Hollingsworth, 2002). The model shown below (Figure 23) is cyclic since change in any one domain may affect another. For instance, someone may enroll in TSDI, engage in the course, experience change in their personal domains, then be motivated to enroll in another course such as TSIR.

Figure 23
Model of Motivation, Engagement, and Professional Growth for Participants of Online Professional Development Courses



Identifying Motivation and Engagement of Participants

First, we determined what motivated these participants to initially enroll in the courses. Determining motivation was done in two ways. Prior researchers have used the responses to enrollment surveys to determine motivation for enrolling in MOOCs (Creager, et al., 2018; Hollebrands & Lee, 2020; Moore & Wang, 2020; Wilkowski, et al., 2014), which was also used in this study. Since there are factors for motivation outside of what is identified on the enrollment survey, the introductory discussion forum was also used to identify reasons for enrolling. Topic modeling was used to identify themes for motivation in introductory discussion forums (see Appendix H and I for code). Computational text mining, such as topic modeling, is a field of learning analytics that has proven effective in analyzing large volumes of text to identify common themes (Silge & Robinson, 2019).

These two results, the responses to the enrollment survey (closed-ended goals) and themes identified by topic modeling (self-stated goals), were then combined as factors for cluster analysis to identify themes for motivation (see Appendix J for code). Cluster analysis is an exploratory analysis method that can be used to classify participants into clusters, or groups, when a classification of groups is not known (Frankowsky, et al., 2015; Gareth, et al., 2017). Cluster analysis has been used by other researchers to group participants of MOOCs based on motivation and engagement (Frankowsky et al., 2015; Thompson et al., 2016; Wiebe & Sharek, 2016).

Click-log data was used to identify patterns of engagement while participants were enrolled in the course. The course management platform records every click, or hit, that a participant does during the course. Prior researchers have used click-log data to examine engagement trends in TSDI (Bonafini, 2018; Lee et al., 2017; Lee et al., 2018; Mojica et al., 2018; Tran & Lee, 2016). These researchers all looked at one course offering at a time. This study combines click log data from all 10 course offerings to identify engagement trends using cluster analysis (see Appendix J). The variables used for cluster analysis are identified in Appendix K.

Follow-up Survey

To gain insight into the professional growth of participants after they have completed the courses, a follow up survey (see Appendix C) was sent out to the 1,592 participants who accessed at least Unit 1 of any of the 10 course offerings. The survey included questions about how the course(s) impacted their statistics teaching practice (domain of practice) and any salient outcomes or changes to their professional life after participating in the course(s) (domain of consequence). The survey includes questions about their beliefs and knowledge about specific topics that are presented in the courses (personal domain). There are questions specific to data investigations (TSDI) and inferential reasoning tasks (TSIR). Participants were only asked to complete the sections specific to the course(s) in which they participated.

Results

Motivation: Why take a course specifically for statistics educators?

The initial discussion forum in each orientation unit asked participants to introduce themselves and say a little about why they were taking the course. Using topic modeling of these responses, self-stated goals for motivation were determined. These include *course specific goals* that are listed specifically in the course descriptions, *continuing their general professional practice* either through earning CEUs, taking the course as a requirement or taking the course again, *pedagogical goals* such as making their classes more engaging or generally improving their teaching, and *learning statistics/increase confidence* in teaching statistics. The largest percent of those that posted in the forum were motivated by *course specific goals*, about 44%.

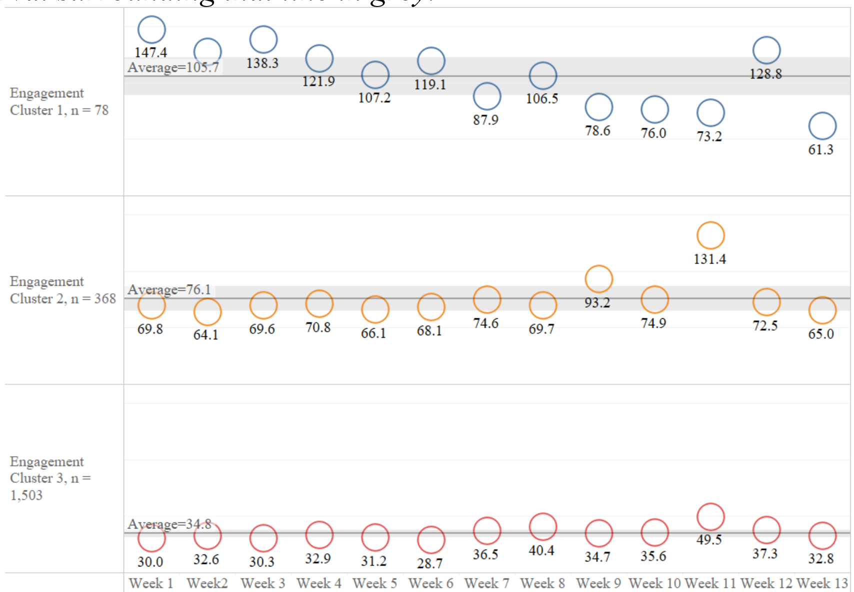
Not all participants posted in the introductory discussion forum, so the enrollment survey was another source of identifying motivation by looking at goals chosen by participants, closed-ended goals (see Appendix G). There were 13 possible closed-ended goals grouped into 4 broad categories; *goals directly linked to course objectives*, *just browsing*, *earn a certificate of completion*, and *goals generic to MOOCs*. Within these broad categories, almost 90% of participants chose a closed-ended goal directly linked to the course objectives as the most motivating reason for taking the course.

Engagement: What did participants do when they were in the course?

Three clusters of participants were identified using cluster analysis of their click-log data, *highly active course completers (HACC), consistent course completers (CCC)*, and *least active course fizzlers (LACF)*. The HACC were the smallest group with 78 participants. Though this group only accounted for a small percentage of participants, they had the most hits in all units, clicked on more resources, and participated in the most discussions. In addition, 67 out of the 78 (86%) made it to Unit 5 in a course. The CCC (368 participants) were not as active as the HACC, but still had a high average number of hits across all units and resources, 244 out of 368 (66%) made it to Unit 5 of a course. The overwhelming majority of participants (n=1,503) were clustered as LACF. Of these only 574 (or 38%) made it to Unit 5. The average number of hits each week (Figure 24), per units and in discussion forums was much lower for LACF.

Figure 24

Weekly average number of hits by participants in each cluster for weeks 1 through 13. The average is determined by the total number of hits for the week divided by the total number of participants that engaged in that week. There is an average line for each cluster, with a 95% confidence interval surrounding that line in grey.



For this study, we also wanted to determine if there was a link between motivation and engagement. Are the reasons people take these courses linked to higher rates of engagement? We did not find evidence to support any claim that different factors for motivation lead to higher rates of engagement. The only relationship was found when the data was filtered to only include those participants who enrolled in TSDI *and* TSIR. In total there were 359 participants who accessed Unit 1 of both courses. Among those participants there was evidence that those whose motivation was linked to course specific goals tended to be among the highly active course completers and those whose goals were not specific to the course were more likely to be least active course fizzlers.

Professional Growth: Where are they now?

The survey was sent out at the beginning of March 2021 and was open for 4 weeks.

Despite monetary incentives and reminders, only 135 opened the survey link, 80 attempted it, and only 50 completed the survey in its entirety. With the challenges and restrictions teachers had during the 2020-2021 academic year caused by the worldwide COVID19 pandemic, it was no surprise that we had such a low response rate. We hope to send this survey out again later, and perhaps get a better response. Nonetheless, these 50 participants give good insight into how these courses affected their professional growth.

Based on enrollment records, 43 of the respondents enrolled in at least one offering of TSDI, 18 had enrolled in at least one offering of TSIR and 12 had enrolled in both courses. The survey responses to which course they enrolled in does not match the enrollment records. In the survey, 36 indicated they had enrolled in at least one offering of TSDI, 15 had enrolled in at least one offering of TSIR, and 10 had enrolled in both courses. (We considered the fact that participants may have forgotten what course they enrolled in, or not considered themselves a participant if they did not reach a certain level of engagement in a course.) When asked to describe their current role as an educator, 28 identified as K-12 classroom teachers, 11 were classroom teachers at a college/university, 3 taught teacher preparation courses at a college/university, and 8 identified as other roles. Twelve of these respondents indicated that this role had changed since they took the course(s).

Survey responses indicated that participants noticed changes in their personal domain because of their participation in TSDI and/or TSIR.

Table **27** shows *some* of the questions that were asked about their knowledge and beliefs. Most participants said they had acquired new skills, knowledge, or resources after being enrolled in either course. One participant reflected, "I felt like the course helped me develop a framework that was helpful in focusing on big ideas, instead of the computational details of procedures".

Another stated, “the courses helped me see statistics as a process beyond just making graphs and calculating things”. Many reflected that it was hard to remember what influence the courses had since they were enrolled so long ago.

Table 27
Sample of questions specific to the personal domain (knowledge, skills and beliefs)

Question	Yes	No	Not Sure
-After engaging in TSDI and/or TSIR did you acquire any knowledge, skills and/or resources applicable to your professional practice?	40	2	8
-Prior to your participation in TSDI, did you have knowledge about the statistical investigation cycle?	19	13	4
-Do you believe it is important for students to engage in all four phases of the cycle when engaging in a statistical investigation?	31	2	3
-Do you believe it is important for students to engage in inference tasks with the general characteristics described in TSIR into your practice?	14	0	0
-Do you believe it is important for students to engage in inference tasks that use the categories of questions described in TSIR into your own practice?	14	0	0

When asked to reflect on any changes to their practice before and after their participation in TSDI, some participants (8) indicated that they had changed their practice by assisting students in the statistics investigation cycle where they had not before taking the course. Those taking TSIR indicated that they had already used questions for inference tasks like those explored in TSIR. But the four characteristics described in TSIR of a good inference task (context, purpose, collect data with multiple variables, and repeated sampling) did not align to their practice before TSIR. In a follow up question about the use of the characteristics of inference tasks in their current practice after taking TSIR, 10 out of 13 said they consider context most of the time and 11 out of 13 consider purpose most of the time. But only 6 out of 13 collect data with multiple variables and 7 out of 13 use repeated sampling in inference tasks. Perhaps some did increase the use of these characteristics in inference tasks after their participation.

Table 28
Sample of questions specific to the domain of practice (i.e. trying new things in the classroom)

Question	Yes	No	Not Sure
-Prior to your participation in TSDI, did you assist students in learning about statistics through engaging in all 4 phases of a statistics investigation?	14	16	6
-Due to your participation in TSDI, do you currently assist students in engaging in all four phases of the statistical investigation cycle?	23	8	5
-Prior to your participation in TSIR, did the characteristics you would use to describe a good inference task align to the general characteristics of context, purpose, collect data with multiple variables, and repeated sampling?	3	6	5
-Prior to your participation in TSIR, did you use inference tasks with the categories of questions described above into your practice?	10	1	3

When reflecting on what practices they implement because of their participation in TSDI, one participant said that when using the statistical investigation cycle, “[s]ome phases are still focused on more than others, but I am able to discuss the big picture more with students”. Unfortunately, others say that engaging in the cycle is limited because of time. Another participant noted that after taking TSIR they are “to the point now where I don't spend time on data and statistics without inference. I have changed my statistical teaching practice to begin with inference using simulations”.

Participants were also asked questions specific to the domain of consequence. These questions addressed sustained changes to teaching, student outcomes and community influence. When asked if their participation in either TSDI or TSIR resulted in any sustained changes to their professional practice, most respondents said that it had (Table 29). One respondent said in their class “I talk about what it means to think and act like a statistician. I for the first time started realizing the difference between a statistician and a mathematician”. Another stated, “I find myself continuously asking students to think about the variability they observe in a data set, how the data collection process impacts the variability, and how we can model the variability to understand better the parameters we might be interested in inferring about".

Table 29

Sample of questions specific to the domain of consequence (long lasting practices, salient outcomes, changes to community of practice)

Question	**Yes**	**No**	**Not Sure**
-Due to your engagement in TSDI and/or TSIR did you make any lasting changes to your professional practice that you are currently implementing?	27	10	12
-Do you believe that your participation in TSDI resulted in any significant changes in your students' outcomes?	5	9	18
-Do you believe that your participation in TSIR resulted in any significant changes in your students' outcomes?	9	1	4

Most participants were not able to say that they noticed a change in student outcomes because of their participation in TSDI or TSIR. An example of a change in student outcomes was given by this participant, "Students are talking more about variation. They are understanding better that the procedures we use are simply tools for assessing unusual variation versus natural variation". Another teacher self-reported that "AP Exam student scores have increased significantly since taking this MOOC [TSIR]".

Another change in the domain of consequence that we were interested in, was how their participation in either course influenced the community around them. This influence may have been encouraging a colleague to take a similar course or redesigning statistics curriculum at their institution based on course material. Of those who indicated they took TSDI, 15 said that they do not believe they influenced those around them, and 7 of the TSIR participants chose the same. But 11 who took TSDI indicated that they had implemented new practices then encouraged others in their department to do so, and 8 from TSDI and 3 from TSIR shared resources they used with other groups, such as professional learning teams. One participant stated "I have developed a series of activities using an online tool that are modelled after activities from this course. I have shared them with a few colleagues and am working to share them at conferences".

Our original goal was to link the findings from the motivation and engagement study to professional growth. We wanted to see if there was some link to what motivated people to take a course or how they engaged in the course to what changed in their personal domains. With so few people taking the follow-up survey it is difficult to generalize about those changes.

Discussion

TSDI and TSIR drew thousands of participants to enroll and had about 1,600 actively engage in at least Unit 1 of at least one of the courses. Participants were able to learn skills to become better statistics teachers while at the same time creating a sense of community with people from all over the world. Our research on motivation showed that participants had a strong desire to learn the objectives of the course, even more than they wanted a certificate of completion. What does this mean for course developers? The participants of these courses were driven to learn what was offered. They were not there just to browse or just to get credits. They valued what was being taught and wanted to learn it. Also, it seems course descriptions really matter. It is important for anyone offering an open online course such as this to be very specific about the objectives of the course. For instance, there were several participants that were there to learn statistics, though learning statistics was clearly not part of the course objectives. Those that were there to "brush up on using p-values" were quickly disappointed. These courses were about pedagogy, not statistical theory. There are plenty of courses out there to teach teachers about statistical theory of concepts (Coursera, n.d.).

Though it is disappointing that most participants had low levels of activity in the courses, it is reassuring that 885 out of the 1,949 participants (45%) who accessed Unit 1 at least looked at material in all five units. This may not seem like a high completion rate when compared to other PD efforts, such as a seated PD in a district setting, where usually all participants start and finish a training. But for MOOCs, this is impressive. Kizilcec et al. (2020) investigated the completion rates of over 250,000 MOOC participants over 2.5 years in over 200 courses from institutions such as MIT, Stanford, and Harvard. They study found that despite many different efforts to improve completion rates, rates steadily stayed around 20%. The participants of TSDI and TSIR may not be actively clicking on every part of the course, but this is evidence that a broader audience than typical MOOCs are seeing most of the materials put forth.

Change in professional growth was evident from the small sample of participants who took our survey. Overall, the results from survey participants showed positive change in the personal domain, domain of practice and domain of consequence. Most participants could recall changes in these domains happening after their participation in TSDI or TSIR, particularly in the personal domain and domain of practice. But it seems that it was hard for these participants to remember if their course participation was a trigger since some took the course over 6 years ago. Hopefully more survey data can be collected soon, as well as interviews, especially since we have evidence from survey responses that people are not able to recall information from earlier course offerings.

So, what is next for online professional development for statistics educators? TSDI and TSIR have been archived and will no longer be offered. Fortunately, Dr. Lee saw the value that participants gained from these courses. In 2021, Dr. Lee and Dr. Gemma Mojica led a new team to release *Amplifying Statistics and Data Science in the Classroom*, an on-demand professional learning resource also hosted at The Place (place.fi.ncsu.edu). This course has two modules with five units each. Module 1 consists of material adapted and enhanced from the original TSDI, and Module 2 consists of materials enhanced and revised from TSIR. The materials have been updated to reflect the most current practices and research in statistics education with an opportunity to earn up to 40 hours of continuing education credits. Unlike the original MOOCs, the *Amplifying Statistics* modules are always open, and participants can access them whenever they want. This also means that groups of statistics educators can use this new professional learning resource to organize learning and engage in self-directed learning or commit to working through modules together on a regular schedule that could involve biweekly discussions and planning for how to improve their practices.

Though the online PD efforts shared here have proven to be fruitful for so many participants, there is still more that can be shared to help those who teach statistics. These two courses covered very important and broad topics in statistics, data investigations and inferential reasoning. Other courses should be created that focus on specific pedagogy. For instance, courses could be created that focus on pedagogy specific to association, probability, data collection and visualizations, and much more. Since many mathematics teachers, especially who teach K-12 students, may have been required to take as few as one statistics course in their teacher preparation program (Franklin et al, 2015), it will be essential for statistics educators to help close that gap to help teachers be more confident to teach statistics.

CHAPTER 7 DISCUSSION

This chapter presents a summary of the findings of this study organized by the two research questions from Chapter 1. This is followed by a discussion of the implications this research has for online professional development researchers and statistics educators. There is a short section acknowledging the limitations of this research, followed by a discussion of future possible research directions.

The *model of motivation, engagement, and professional growth of OPD courses* (see Figure 4) was used as a framework for this study. I first explored motivation and engagement of participants in TSDI and TSIR using topic modeling and cluster analysis (Chapter 4 and 5). Then professional growth of participants was analyzed through a follow up survey sent to participants at least a year after they had engaged in either course (Chapter 6).

Summary of Research Question 1

How can participants across two online professional development courses for teachers of statistics be characterized based on their motivation for taking the course(s) and their engagement during the course(s)?

The journal ready manuscript in Chapter 5 answered this question by clustering participants of this study by motivation and engagement. The first sub question was answered by identifying three groups based on motivating factors.

1a. What motivates participants to enroll in online professional development courses for statistics educators?

Chapter 5 used two sources of data to cluster participants based on their motivation to enroll in either TSDI or TSIR, self-stated goals and closed-ended goals. The first source of data, closed-ended goals, were the answers to a question on the enrollment survey, that asks participants why they enrolled in the course. The second source of data, self-stated goals, were topics identified through topic modeling of the introductory discussion forums. Chapter 4 presented a thorough exploration of the methodologies used for topic modeling and their efficacy, to answer a secondary sub question.

1a.i. In what ways can topic modeling be an effective tool to identify motivation of participants who enroll in online professional development courses for statistics educators?

I hypothesized that participant posts in the introductory forum would be another source of data to identify participant motivation. In this forum, most of the participants of the study stated why they initially enrolled in the course. There ended up being 946 posts related to motivation. In Chapter 4, topic modeling of these posts was used to identify themes as an alternative to traditional qualitative coding of data. After an initial exploratory topic modeling process, three topic modeling procedures were used to identify themes for motivation. Method 1 utilized an unsupervised learning method to identify themes for motivation. Method 2 used a semi-supervised learning method that used a seeded dictionary of terms based on qualitative coding of 10% of the posts. Method 3 used the same results of Method 2, with topics collapsed to general themes aligned with goals listed on registration survey. For each of the methods, each post was assigned a theme, then checked to see if the theme seemed appropriate or not to the post, to assign a *validity score* (the percentage of posts that were correctly assigned to a theme). The results showed that Method 1 outperformed Method 2, 61.0% to 48.9%. But Method 3 outperformed Method 1 and 2, with a validity score of 75.8% (see

Table 12).

The themes identified in Method 3 were then used as part of the cluster analysis (since it had the highest validity score) to identify groups of participants based on motivations for taking the course. Each participant was assigned 1 of the following four themes; *course specific goals* (goals that aligned to the objectives for either course), *continuing professional learning* (continuing their professional practice, by earning CEUs, or taking the course again/reenrolling in a course), *pedagogical goals* (enrolled to become a better teacher), and *learn statistics/increase confidence* (either brush up on statistics skills or become a more confident statistics instructor).

The goals from topic modeling (self-stated goals) were then combined with goals from the enrollment survey (closed-ended goals) to create a *motivation matrix* that included each participant. This matrix was used to perform k-means clustering. Chapter 5 presents the process of the clustering analysis as well as a discussion of how the clusters found were used to identify three groups of participants based on their motivation for taking TSDI or TSIR. To answer research question 1b, participants of this study were identified as *professional learners for teaching statistics, statistics investigators,* or *teaching resource collectors* (see

Table **16**). *Professional learners for teaching statistics and statistics investigators* tended to choose goals specific to TSDI (in fact all these participants that were *statistics investigators* had enrolled in TSDI). *Teaching resource collectors* were more interested in collecting tools and resources for their practice.

1b. How do participants of OPD for statistics educators engage in the courses?

The second sub question for research question 1 sought to group participants by how they engaged in the course. Chapter 5 includes the methodology and analysis of groups identified through cluster analysis of click-log data, collected while the participants engaged in the courses. This data was first cleaned to include the number of *hits* a participant had for each week, in each unit, and across different types of pages (such as discussion forums, resource pages, videos, etc.). K-means clustering was again used to cluster participants based on an engagement matrix that was created based on 83 variables identifying a participant's engagement.

Three groups of participants were identified by the methodology and analysis shared in Chapter 5 (see

Table 21). The three groups were *highly active course completers* (HACC), *consistent course completers* (CCC), and *least active course fizzlers* (LACF). The HACC group was the smallest, 78 (~4% of participants). This group included participants with the highest activity throughout all weeks, units and pages, as well as having the highest rates of completion (either defined as earning a certificate of completion or accessing Unit 5). The CCC group had 368 participants (~19% of participants). This group was not as active as the HACC but tended to consistently visit the course over the weeks and units. Though their completion rate was not as high as HACC, most participants completed a course. The LACF were the largest group with 1503 participants (~77% of participants). These participants had very low participation rates across all variables. They tended to come to the course around unit 1 and fizzle out. Very few of these participants reached the end of a course.

1c. How is motivation for enrolling in OPD for statistics educators related to how participants engage in the course(s)?

The final sub question for research question 1 was an attempt to identify any relationship between motivation for enrolling in a course and how a participant engaged in the course. This comparison is shared in Chapter 5. To answer this question, the 3 groups identified for motivation and 3 groups identified by engagement were compared (see Table 22 and Table 23). I hypothesized that those who were motivated by course specific goals, the *professional learnings for teaching statistics* and *statistics investigators*, would be more engaged. It was found that there was no clear relationship between the groups. There were fairly equal representations of each group when broken down by motivation or engagement.

A relationship among motivation and engagement did emerge when participants were broken down by course participation, particularly those that enrolled in TSDI *and* TSIR. When looking at participants who had enrolled in TSDI and TSIR, a higher percentage of HACC tend to be *statistics investigators* (50%) compared to the *professional learners for teaching statistics* or *teaching resource collectors* (34.6% and 15.4% respectively). Additionally, a much higher percent of CCC tends to be *professional learners for teaching statistics* (61.1%) than the other motivation clusters. The percent of *teaching resource collectors* per engagement cluster is not higher than 26.2%. This result shows that those people who enrolled in both courses and are either *professional learners for teaching statistics* or *statistics investigators* tend to have higher levels of engagement and higher rates of course completion (defined as accessing Unit 5). Those who were motivated by goals related to the course objectives tended to be more actively engaged in the course. There were so few participants enrolled in TSIR only that those comparisons between motivation and engagement clusters were not shared in Chapter 5.

Summary of Research Question 2

How did participation in statistics education online professional development impact ongoing professional growth for participants?

The *model of motivation, engagement, and professional growth of OPD courses* (see Figure 4) includes the *Interconnected Model of Professional Growth (IMPG)* (see Figure 1). The IMPG is used to locate "change" that occurs in the three domain of the teacher's professional world (personal domain, domain of practice and domain of consequence). These domains are affected by an external domain that acts on them. A survey was sent to all participants with questions specific to the personal domain, domain of practice and domain of consequence, to describe any impacts of professional growth of practices after engaging in TSDI and/or TSIR.

Chapter 6 explores the results of the survey from 50 respondents. Though this is a small representation of the total amount of participants in the study, it still provides a good snapshot of ongoing professional growth. Overall, most survey respondents indicated they had noticed change in their personal domain and domain of practice. Forty respondents indicated they had acquired knowledge, skills, and beliefs relevant to their professional practice (see Table **27**). Respondents also believe that engaging students in the statistics investigation cycle (the focus of TSDI) and engaging students in inferential reasoning tasks (the focus of TSIR) are important. As far as the domain of practice, participants in TSDI who had not previously engaged students in statistics investigation cycles, now include it in their practice (see Table **27**). Participants in TSIR had not used general characteristics of a good inference task that were shared in materials for the course, but reported they now tried to include those characteristics.

When analyzing survey question results specific to the domain of consequence, there was not strong evidence showing a change in this domain after participating in TSDI and/or TSIR. Survey questions specific to the domain of consequence asked participants about sustained changes to their teaching practice, student outcomes, and community influence. Many participants noted that they could not remember if changes they noticed were a result in participation in the courses or a result of some other external influence. Most said their teaching practice changed because of participation (see Table 29), but most could not identify if they had changes in student outcomes or if their participation had influenced other educators around them.

Implications

Using the model of motivation, engagement, and professional growth of participants in OPD courses provided the opportunity to investigate why participants enrolled in TSDI or TSIR, what they did when they engaged in the course, and how the course(s) may have impacted their professional growth after taking the courses. Framing the research with this model also gave opportunities to use various analysis methods to describe participants interactions with the course(s). The implications of this study not only provide insights to future statistics educators on the value OPD courses, but it also provided thorough descriptions of methodologies that other researchers may find useful when analyzing participants patterns of interactions in open OPD courses.

Researchers have often used an enrollment survey in open online courses to determine what motivates people to join courses (Creager, et al., 2018; Hollebrands & Lee, 2020; Moore & Wang, 2020; Wilkowski, et al., 2014). This study found that the introductory discussion forums were another source of determining motivating factors that may exist outside of an enrollment survey. Topic modeling was chosen as an alternative approach to typical qualitative analysis methods, to identify these themes for motivation. Ferreira-Mello et al. (2019) provided a systematic literature review of studies in the educational text mining field. One of the questions they sought to determine was what text mining methods and techniques the field of education used to analyze the large corpus of texts that are available in open courses such as MOOCs. Text classification (such as the topic modeling techniques shared in Chapter 4), and natural language processing were the most used. Ferreira-Mello et al. (2019) state, “the majority of educational text mining literature is more focused on the output than the process” (p. 10). It is my hope that the methods shared in Chapter 4 give a clear insight into the *process* of using topic modeling for other researchers seeking to identify themes through topic modeling of large qualitative datasets.

Isoaho, et al. (2021) warn researchers who use topic modeling that the interpretation of the topics must not be independent of the data source. In the topic modeling techniques used in this study, the content of the discussion forums had to be considered as a part of this process. Research on topic modeling of discussion forum data from MOOCs is often done by researchers who were not part of the development of the MOOCs or not familiar with the topics of the MOOC (Isoaho et al., 2021). The themes identified in this study would probably have not come about from a researcher not familiar with the data. Text mining will not fully replace traditional qualitative analysis, but hopefully this study shows how it can be used as a complement to the research when used appropriately.

Self-determination theory is often used as a framework for researchers investigating motivations for enrolling in a MOOC, using intrinsic and extrinsic motivations as basic themes (Moore & Wang, 2020; Wiebe & Sharek, 2016). Once the two sources of data, enrollment survey responses and topic modeling themes, were combined to identify groups of participants by motivation using cluster analysis, two themes emerged that went beyond intrinsic and extrinsic motivations. Participants were either motivated by goals that were specific to the objectives of the courses, or they were motivated by other factors such as collecting resources for teaching. These themes do not fall under extrinsic or intrinsic motivations, because within the description of each group there are factors of both extrinsic and intrinsic motivation.

It may be argued that most participants chose goals from the enrollment survey that were like the course objectives they read when enrolling, so they naturally chose those answers. But adding in the topic modeling themes, one of which was specific to course objectives, helps to support the claim that this did not just happen by chance. This finding is important to people developing online professional learning courses. Course developers should recognize that course descriptions and objectives should be transparent and clear when people are enrolling. If a participant wants to learn something that is written in the objectives, and that topic is not clearly covered, this may lead to participants leaving the course.

When defining course completion as reaching Unit 5, this study shows that participants in TSDI and TSIR completed the course at higher rates than typical MOOCs. Research has shown that typical MOOC completion rates are around 20% (Kizilcec, et al, 2020), but for TSDI and TSIR, 885 out of the 3,815 enrollees reached Unit 5 (23.2%). This is not that much higher than typical. But when we define the participants as those that accessed at least Unit 1 (the first unit with content material), and not include the "browsers", the completion rate is 885 out of 1,949 (45%). Perhaps MOOC researchers should focus their research on these people, and not include browsers when calculating completion rates.

For those who are considering creating online PD for statistics educators, the completion rate findings, and the evidence of professional growth after engaging in TSDI or TSIR should be a motivating factor to create similar PD opportunities. For those who are seeking out PD for teaching statistics, online opportunities can be convenient and effective ways to learn skills necessary to teach statistics. The SET report (Franklin et al., 2015) recommends that PD for statistics teachers should be able to develop a deep conceptual understanding of the statistics they will teach, and they should be actively engaged in the statistical investigation cycle. Evidence from the follow-up survey (Chapter 6) show that participants engaged in the statistical investigation cycle during the online PD and still make it a part of their practice. The materials in both courses were also presented in a way to help develop deep conceptual understanding of teaching statistics. The outline and methods used in these courses (such as engaging in a statistics task as a student, providing videos of other statistics educators discussing big topics) could prove useful for others creating OPD opportunities for teachers of statistics.

Darling-Hammond et al. (2017) listed *sustained duration* as one of the recommendations for effective teacher professional development. Offering two successive online PD courses specifically for statistics educators, is a novel approach to PD in general. It also meets the recommendation of sustained duration. There was no evidence that there were changes in professional growth specific to those who enrolled in both courses since there were so few respondents to the survey. But there is evidence that those who engaged in TSDI *and* TSIR generally were more active in the courses and had higher completion rates. Having the opportunity to engage in two courses seemed to help some participants.

These two courses are certainly helpful in meeting the recommendations for PD for teachers of statistics, but they are not inclusive of *all* big topics that teachers teach. Future course developers should take the lead from these courses when thinking about big ideas that could be covered. For instance, there were those in the survey that responded that they did aid students in the statistics investigation cycle, but collecting data was the part of the cycle they used the least. GAISE II (Bargagliotti, et al., 2020) highlights skills necessary for making sense of data today, which includes how to collect and clean data and considering different variable types. Since there seems to be a gap to fill in incorporating data collection in the investigation cycle, perhaps there could be another course focused on this.

Future Research Directions

The model of Motivation, Engagement, and Professional Growth for Participants of OPD Courses that guided this study was conceptualized to be cyclic. The general model of engagement (Wiebe & Sharek, 2016) situated engagement in between motivation and learning in a linear model. I proposed a cyclic model with the idea of TSDI and TSIR in mind. I hypothesized that participants could engage in this cycle over and over. For instance, a participant may be motivated to take TSDI for some reason, engage in the course, experience professional growth in one or more domain, then be motivated again to take TSIR based on that previous cycle. Unfortunately, limitations to data collection did not allow for evidence for this process to be accessed. Future research could include interviews of a chosen sample of participants who took TSDI and TSIR, and describe their motivation, engagement, and professional growth through this cyclic model. A case study could be a useful approach to a study of that sort.

The text mining approach used in this study only addressed the introductory discussion forum. Each course had 10 other forums that also include a wealth of information that could be used in future studies. Topic modeling approaches like those described here could identify more general themes of what participants are learning in the courses. For instance, in Unit 3 of TSIR, participants are asked to explore a multivariate dataset about vehicles using "their favorite data analysis tool" and are given the option to use CODAP. It would be interesting to see what other tools people are using to do this data investigation. A seeded dictionary could be built identifying known data analysis tools, then used on data from this forum in all 3 course offerings of TSIR, to see what people used for analysis and the insights they gained about characteristics of vehicles.

This could give more insight into the technology tools that people tend to use when exploring data.

Though the sample of participants who took the follow-up survey was small, there was still evidence from this sample that there was difficulty recalling their participation in the courses and what part of their personal domain, domain of practice or domain of consequence were affected by their participation. The new *Amplifying Statistics and Data Science in the Classroom* open course is now available at The Place. Those participants in that course may be a better sample to survey about their professional growth. The survey could be sent out to those participants a set amount of time after they have completed at least one module and had time to implement what they learned into their practice. These findings could be used to continually update that open course as well as provide direction of what subjects could be covered in future course offerings.

In any of these suggested studies, the same questions remain; why are people here, what are they doing when they are here, and what are they taking with them when they leave? The first two questions, centered on motivation and engagement, may take a lot of time and effort to analyze, but that data seems to be available, the right questions and methodologies must be used to get there. Identifying professional growth after participants have completed open OPD is much harder to do, especially since participants can be from all over the world. Though it can be difficult, this will be useful information for future online PD course developers in designing effective professional development.

As the role of statistics in mathematics curriculum increases, so does the need for increased PD for those who teach statistics. Likewise, as access and quality of online courses increases, so too does access to online professional development for educators. It is only a matter of time that online professional development opportunities specific to statistics also increases, and I hope that findings from studies such as this can help aid in the development of those future course offerings.

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APPENDICES

Appendix A – Teaching Statistics Through Data Investigations Enrollment Survey

Question	Code	Type	Options
Have you engaged in other professional development that is related to preparation for teaching statistics?	tsdi-other-pd	Radio	Yes No
If yes, please briefly describe the professional development.	tsdi-pd-descrip	Text	
How much experience do you have with teaching statistical concepts (in a statistics course, or units on statistics within a course, etc.)?	tsdi-experience	Radio	No experience Very little experience Some experience A lot of experience
Please enter the total number of statistics classes that you have taken at a college or university (both undergraduate and graduate levels)? (Please round to the nearest whole number.)	tsdi-classes	Text	
Which of the following best describes your primary reason for enrolling in this course?	why-enroll	Select w/other option	Just browsing Deepen my knowledge of the course topic(s) Connect with peers/colleagues Collect resources and tools for my practice Earn a certificate of accomplishment/renewal credits
How familiar are you with micro-credentials?	mc-familiarity		I am not familiar with micro-credentials I am familiar, but have not earned a micro-credential I have earned micro-credentials previously

Appendix B – Teaching Statistics Through Inferential Reasoning Enrollment Survey

Question	Code	Type	Options
Have you engaged in other professional development that is related to preparation for teaching statistics?	tsdi-other-pd	Radio	Yes No
If yes, please briefly describe the professional development.	tsdi-pd-descrip	Text	
How much experience do you have with teaching statistical concepts (in a statistics course, or units on statistics within a course, etc.)?	tsdi-experience	Radio	No experience Very little experience Some experience A lot of experience
Please enter the total number of statistics classes that you have taken at a college or university (both undergraduate and graduate levels)? (Please round to the nearest whole number.)	tsdi-classes	Text	
Which of the following best describes your primary reason for enrolling in this course?	why-enroll	Select w/ other option	Just browsing Deepen my knowledge of the course topic(s) Connect with peers/colleagues Collect resources and tools for my practice Earn a certificate of accomplishment/renewal credits
How familiar are you with micro-credentials?	mc-familiarity	Radio	I am not familiar with micro-credentials. I am familiar, but have not earned a micro-credential. I have earned micro-credentials previously.
How did you hear about this MOOC-Ed?	referral	Select w/ other option	Administrator/supervisor Colleague/peer Conference

The Friday Institute, staff
The Friday Institute, program
The Friday Institute, email
The Friday Institute, social media
Digital Promise
Future Ready
Google ad
Search engine (Google, Bing, etc.)
State Department of Education

Appendix C – Sample Invitation Letter

Dear <name>,

As part of a research study at NC State University, I am asking individuals who participated in the *Teaching Statistics Through Data Investigations (TSDI)* or the *Teaching Statistics through Inferential Reasoning* (*TSIR*) courses, such as yourself, to complete an online survey regarding your current professional practice. The information you provide is crucial to helping us better understand the professional growth that participation in online professional development has on teachers of statistics.

As a thank you for your time, participants will be randomly chosen to receive a $100 gift card. A random drawing will be held for every 100 participants who complete the survey. The survey is expected to take 20-30 minutes. All responses will be anonymous.

You will have the option to indicate if you are also interested in participating in a follow-up study that will include submitting tasks that you currently use and participating in 45-minute interview. Compensation for submitting tasks and participating in the interview will be **a $50 gift card.**

To participate, please click the following link:

<link>

Your participation will be a great help in this study!

If you have any questions about this survey, or difficulty in accessing the site or completing the survey, please contact Heather Barker at heather.barker@ncsu.edu.

Appendix D – Electronic Consent Form

North Carolina State University
INFORMED CONSENT FORM for RESEARCH

Title of Study: Motivation, Engagement and Professional Growth of Participants in Online Professional Development Courses for Statistics Educators
Principal Investigator: Heather Barker
Adviser: Dr. Hollylynne Lee

What are some general things you should know about research studies?
You are being asked to take part in a research study. Your participation in this study is voluntary. You have the right to be a part of this study, to choose not to participate or to stop participating at any time without penalty. The purpose of this research study is to gain a better understanding of the professional growth of participants of online professional development courses for teachers of statistics.

You are not guaranteed any personal benefits from being in a study. Research studies also may pose risks to those who participate. In this consent form you will find specific details about the research in which you are being asked to participate. If you do not understand something in this form it is your right to ask the researcher for clarification or more information. A copy of this consent form will be provided to you. If at any time you have questions about your participation, do not hesitate to contact the researcher(s) named above or the NC State IRB office as noted below.

What is the purpose of this study?
The purpose of this study is to investigate the ongoing professional growth of participants who participated in the online courses *Teaching Statistics through Data Investigations (TSDI)* and/or *Teaching Statistics through Inferential Reasoning (TSIR)*. Previous studies have found positive evidence that the courses have had on the knowledge, beliefs and attitudes of participants. This study intends to examine if there is a lasting affect on the professional practices of participants in these courses. The information you provide is crucial to helping us better understand the professional growth that participation in online professional development has on teachers of statistics. This research hopes to help educators better understand the current practice of teachers of statistics, the effect that online professional development has on participants, and inform other developers of PD for teachers of statistics.

Am I eligible to be a participant in this study?
In order to be a participant in this study you must have participated in TSDI and/or TSIR between Fall 2015 and Spring 2019.

What will happen if you take part in the study?
If you agree to participate in this study, you will be asked to complete an online survey regarding your current practices. The survey is expected to take 30-40 minutes. AT the end of the survey, you will have the option to indicate if you are willing to participate in a further study. If you

consent, the additional study will ask you to submit tasks that you use in your current practice and participate in a 45 minute follow-up interview.

Risks and Benefits

There are minimal risks associated with participation in this research. There are no direct benefits to your participation in the research. The indirect benefits may include reflection on your teaching practices and beliefs, leading to a better self-understanding and awareness.

Confidentiality

The information in the study records will be kept confidential to the full extent allowed by law. Data will be stored securely in password-protected Qualtrics and/or Google accounts. No reference will be made in oral or written reports which could link you to the study.

Compensation

You will have the opportunity to be entered into a random drawing for a $100 gift card. For every 100 survey participants, there will be a random drawing for a $100 gift card. To be eligible for a gift card, you must submit the survey, and then provide an email address at which you can be contacted. Your email address will not be able to be connected with your survey responses.

If you indicate interest in participating in the follow-up study, your name and email address will be temporarily linked with your survey data. This will be removed and replaced with an ID code. If you submit a task and participate in an interview, you will receive a $50 gift card. If you decide to withdraw from the study during the interview, the $50 compensation will not be received.

What if you have questions about this study?

If you have questions at any time about the study itself or the procedures implemented in this study, you may contact the researcher, Heather Barker heather.barker@ncsu.edu, or at Duke 201B, Elon University, Elon, NC 27244, or by phone 919.744.4736

What if you have questions about your rights as a research participant?

If you feel you have not been treated according to the descriptions in this form, or your rights as a participant in research have been violated during the course of this project, you may contact the NC State IRB Office via email at irb-director@ncsu.edu or via phone at 1.919.515.4514. You can also find out more information about research, why you would or would not want to be in research, questions to ask as a research participant, and more information about your rights by going to this website: http://go.ncsu.edu/research-participant

Consent to Participate

"I have read and understand the above information. I have received a copy of this form. I agree to participate in this study with the understanding that I may choose not to participate or to stop participating at any time without penalty or loss of benefits to which I am otherwise entitled."

Appendix E – Follow Up Survey for TSDI and TSIR Participants

After each question, written in red, is an indicator of which parts of the framework the question will help to describe.

This survey is designed to evaluate the long-term effect that your participation in the online courses *Teaching Statistics through Data Investigations* (*TSDI)* and/or *Teaching Statistics through Inferential Reasoning (TSIR)* has had on your professional life. I am interested in hearing about changes in your teaching practice and other salient outcomes that are a result of your participation in these courses. I hope this research will help inform the creation of online professional development experiences for educators.

Once completing the survey, you will have a chance to be entered into a drawing for a $100 gift card that will be given out to randomly selected participants. A $100 gift card will be given out for every 100 survey participants.

Your name is only being collected to match your survey results with the data we have already collected while you were taking the course. Your name will be de-identified after data collection is complete.

Name:

Part 1: Changes in Practice

I am interested in how your participation in TSDI and/or TSIR has influenced your teaching practices. I will first ask general questions about your role as an educator. Then questions will address your professional practice followed by specific questions based on which of the courses you took.

1. Which of the following best describes your current role as an educator?
   - Classroom Teacher - K - 12
   - Classroom Teacher - College/University
   - Professional Development
   - Curriculum and Instruction Support
   - Instructional Technologist
   - Teacher Preparation - College/University
   - Student - College/Graduate
   - Researcher
   - Other: (please describe)
2. Has your current role as an educator changed since participating in TSDI/TSIR?
   - Yes
   - No
   - Not sure

3. After engaging in TSDI and/or TSIR did you acquire any knowledge, skills and/or resources applicable to your professional practice? (Personal Domain)
   - Yes
   - No
   - Not sure
   - 3a. Please explain your selection:
4. After engaging in TSDI and/or TSIR did you make any lasting changes to your professional practice that you are currently implementing? (Domain of Practice)
   - Yes
   - No
   - Not sure
   - 4a. Please explain your selection:

5. Consider the total amount of time you currently spend in your practice teaching students (or educators) about big ideas in statistics (such as measures of central tendency and variation, hypothesis testing, etc.). When learning new ideas how often are your students presented with the following? (Domain of Practice)

   None(1) A little (2) A moderate amount (3) A lot(4)

   Formulas necessary to produce numerical summaries of data.
   Step-by-step procedures for computing answers to problems.
   Driving statistical questions that can be answered with new statistical concepts.
   Real (and messy) data to explore and manipulate.
   Hands-on manipulatives for exploring a new concept.
   Using technology to introduce new ideas.
   Questions to make students think critically about the importance of a new concept.

6. Please rate the extent to which you agree or disagree with each of the following statements as you reflect on your own teaching practice. (Personal Domain)

   Strongly Disagree(1) Disagree(2) …… Agree(5) Strong Agree(6)

   Students should learn fewer topics at a greater depth than those that are required in the curriculum I teach
   -A deeper conceptual understanding of statistics is not necessary for the curriculum I cover.
   -I do not have time in my current practice to cover topics at a deeper level of understanding.
   -I would like to teach statistics concepts at a deeper level of understanding, but I do not feel comfortable enough with my own level of understanding to do so.
   -It is not necessary to teach statistics concepts at a deeper level of understanding since the required assessments for my students only require calculations for statistics.

7. In your current professional practice, when teaching statistics, how often do you incorporate the following technologies? (Domain of Practice, incorporating technology)

   Never(1) A little (2) A moderate amount (3) A lot(4) Most of the time(5)

   -Graphing calculator with built in statistical functions
   -Statistical software packages (e.g. Minitab, R, SPSS, JMP, StatCrunch…)
   -Web Applets (e.g. StatKey, Rossman/Chance)

-Educational software (e.g. TinkerPlots, Fathom, CODAP)
-Multimedia materials (e.g. Youtube videos)
-Collaboration tools (e.g. Google Docs)
-Education assessments (e.g. MyStatLab, Webassign)
-Other:

7a. Please elaborate on any of the choices above.

8. What are your reasons for not using technology other than graphing calculators in your course? (Select all that apply.) (Domain of Practice, incorporating technology)
   there is no computer technology available
   there are constraints on technology use in my educational setting
   students are already provided with statistical output in their textbooks or assessments
   students use hand-held calculators to compute statistics using formulas
   there is not enough time to incorporate technology outside of calculators
   students are not comfortable enough or skilled enough with technology tools
   I am not comfortable enough or skilled enough with technology tools
   Other (please describe below):

9. In thinking about your current teaching practice, how often do you use technology to do the following? (Domain of Practice, incorporating technology)

Never(1)   A little (2)   A moderate amount (3)   A lot(4) Most of the time(5)

- Promote collaboration and student involvement, (e.g.Google docs)
- Automate calculations for quicker analysis
- Collect data (e.g. using survey tools or probeware)
- Access and import real data (e.g. Finding data sets from the web)
- Data exploration (e.g. generating multiple graphs or numerical summaries to compare groups)
- Visualization of abstract concepts (e.g. dragging points on a scatterplot to observe changes in the regression line or r)
- Simulations as a pedagogical tool (e.g. generating multiple samples to explore properties of the sampling distribution)

Did you participate in *Teaching Statistics through Data Investigations (TSDI)?*

- o Yes (if chosen, redirect to TSDI section)
- o No (if chosen, go to TSIR question)

Section for going straight to TSIR

Did you participate in *Teaching Statistics through Inferential Reasoning?*

- o Yes (if chosen, redirect to TSIR section)
- o No (if chosen, go to end of survey, not to section for participating in follow-up)

Section A: Questions specific to TSDI

Statistical Investigation Cycle

The statistical investigation cycle includes four phases: posing questions, collecting data, analyzing data, and interpreting results.

1. Prior to your participation in TSDI, did you have knowledge about the statistical investigation cycle? (Personal Domain)
   - o Yes
   - o No
   - o Not sure
2. Prior to your participation in TSDI, did you assist students in learning about statistics through engaging in all 4 phases of a statistics investigation? (Domain of Practice)
   - o Yes
   - o No
   - o Not sure
   - o 2a. Please explain
3. After your participation in TSDI, do you currently assist students in engaging in all four phases of the statistical investigation cycle? (Domain of Practice)
   - o Yes
   - o No
   - o Not sure
   - o 3a. Please explain
4. Do you believe it is important for students to engage in all four phases of the cycle when engaging in a statistical investigation? (Personal Domain)
   - o Yes
   - o No
   - o Not sure:
   - o 4a. Please explain:
5. On a scale of 0 - 4 (0 being never and 4 being always) how often do you currently incorporate each of the 4 phases into statistical investigations? (Domain of Practice)

	never	very rarely	sometimes	most of the time	always
posing questions					

collecting data
analyzing data
interpreting results

5a. Provide any comments you think are relevant to your selection above.

Statistical Habits of Mind

6. Think about statistics tasks you use in your current teaching practice. Consider each of the habits of mind listed below and rank how often you promote the development of that habit of mind? Rank the following habits of mind on a scale of 0 to 4, with 0 being never and 4 being always. (Domain of Practice)

never very rarely sometimes most of the time always

Context:
ask contextually-based questions that call for the use of data to answer.
Variability:
seek to explain and control variability.
Measurement:
Consider how to best measure attributes in a context for answering a question. Use appropriate tools (physical and online) to collect and manage data.
Sampling:
Consider sample size – it matters. Use random sampling to help control bias. Identify and account for sources of potential variability in data collection methods.
Visuals:
Use appropriate tools strategically for creating multiple representations.
Variability:
Coordinate graphs and statistical computations to reason about distributions in the aggregate.
Trends:
Look for patterns and relationships within and among variables.
Context:
Consider context of your question to identify measurement issues (missing data, outliers). Make a claim connected to the context of the questions.
Uncertainty:
Account for uncertainty in a claim (be confident but not certain).
Skeptic:
Check the reasonableness of a claim (skepticism)

6a. Provide any comments you wish about the selections above.

7. Consider the answers you provided for the previous answers. Has the incorporation of statistical habits of minds in the tasks you use in your practice changed because of your participation in TSDI? (Domain of Practice)

    - No, my tasks remained the same before and after my participation.
    - Yes, I changed some of my tasks to incorporate the statistical habits of mind above.
    - Yes, I consistently consider statistical habits of mind in creating tasks because of my participation in TSDI.
    - Provide any comments on your selection

8. Please provide any further information on how you use what you learned from your participation in TSDI into your current practice. (Domain of Practice)

9. Did you also participate in the Teaching Statistics through Inferential Reasoning (TSIR) course?

    - Yes (redirect to the TSIR section)
    - No (redirect to part 2)

Section B: Questions specific to the TSIR course

In TSIR, participants learned how to emphasize inferential reasoning in teaching statistics through posing different types of investigative questions. I am interested in evaluating how participants incorporated general characteristics of an inference task and categories of investigative questions to pose into their current professional practice.

General characteristics of an inference task

1. Think about statistics tasks you use in your current teaching practice. Consider each of the general characteristics of a task listed below and rank how often you consider that characteristic when creating a task? Rank the following on a scale of 0 to 4, with 0 being never and 4 being always. (Domain of Practice)

never very rarely sometimes most of the time always

- **Context** – choose contexts that are appealing and approachable for students. When possible have students collect their own data or when the data is already collected, be sure students have an opportunity to consider all characteristics of the data and experiment design.
- **Purpose** – ensure that there is a meaningful purpose or reason for the task to make an inference.
- **Collect data with multiple variables** – using data with multiple variables (both quantitative and categorical) allows students to explore trends and relationships as well as determining the affects subgroups may have on those trends.
- **Repeated sampling** – whenever possible provide opportunities for repeated sampling so that the variability among samples can be experienced and accounted for when making inferences beyond a sample.

1a. Provide any comments you wish about the selections above.

2. Prior to your participation in TSIR, did the characteristics you would use to describe a good inference task align to the general characteristics described above (context, purpose, collect data with multiple variables, and repeated sampling) ? (Personal Domain)

- Yes
- No
- Not sure

1. Do you believe it is important for students to engage in inference tasks with the general characteristics described above into your practice? (Personal Domain)

- Yes
- No
- Not sure:
- 4a. Please explain:

Categories of investigative questions to pose

2. Think about the statistical inference tasks that you currently use in the tasks/lessons you use in your practice. How often do you use categories of questions that are described below, when creating and implementing your tasks/lessons? Rank the following categories of questions. (Domain of Practice)

	never	very rarely	sometimes	most of the time	always

- **Comparing Groups** – trying to identify the similarities or differences between groups is a natural inquiry for most people. Asking questions that require students to compare groups are a good way to introduce students to inference.

- **Samples to Populations –** when trying to make a claim about a larger population based on a sample, students must be able to consider sampling techniques. It is also important in these questions for students to consider sampling variability and how statistical measures vary from sample to sample.

- **Competing Models** – these types of questions could include asking which type of distribution a data has or what type of probability model may have generated the data. These questions ask students to consider the best way to describe data.

4a. Provide any comments about your selections above:

3. Prior to your participation in TSIR, did the categories of questions you would ask in an inference task align to the categories of questions described above (comparing groups, samples to populations, and competing models) ? (Domain of Practice)

   - Yes
   - No
   - Not sure

4. Prior to your participation in TSIR, did you use inference tasks with the categories of questions described above into your practice? (Domain of Practice)

   - Yes
   - No
   - Not sure
   - 2a. Please explain

5. Do you believe it is important for students to engage in inference tasks that use the categories of questions described above into your own practice? (Personal Domain)

    - Yes
    - No
    - Not sure:
    - 4a. Please explain:

6. Please provide any further information on how you use what you learned from your participation in TSIR into your current practice. (Domain of Practice)

Part 2. Professional Outcomes after participating in TSDI/TSIR

I am also interested in other ways that your participation in TSDI and/or TSIR has impacted you professionally. Prior research on TSDI/TSIR has shown the positive impact that engaging in the course had participants' knowledge, beliefs and dispositions and intended change in practice. But research has not investigated the long term effect that participation in these courses have had on participants professionally.

Salient Outcomes

In describing professional growth, salient outcomes are often tied to innate changes in one's value system. For instance, a teacher experiments with implementing data investigations into their class and notices that students respond positively to the new practice. The teacher then makes using data investigations a regular part of her practice after realizing the value this practice has on students.

1. Using the description above as an example of salient outcomes, do you believe that your participation in TSDI resulted in any sustained changes in your professional practice? (Domain of Consequence)
    - Yes
    - No
    - Not sure
    - I did not participate in TSDI
2. Please describe any sustained changes to your professional practice as a result of your participation in TSDI. (Domain of Consequence)
3. Using the description above as an example of salient outcomes, do you believe that your participation in TSIR resulted in any sustained changes in your professional practice? (Domain of Consequence)
    - Yes
    - No
    - Not sure

- I did not participate in TSIR

4. Please describe any sustained changes to your professional practice because of your participation in TSIR. (Domain of Consequence)

5. Besides your participation in TSDI/TSIR, have you participated in other opportunities for professional development specific to teaching statistics? (please choose all that apply) (Domain of Consequence)

- Read journals/websites specifically for statistics educators (ex. Statistics Education Website, CAUSE Web, Statistics Teacher Journal of ASA)
- Joined statistics educator groups (i.e. became a member of ASA, attend regular meetings with other statistics educators)
- Live or pre-recorded webinars (online seminars)
- Workshops
- In-person short courses/mini-courses
- Online professional development course
- Graduate courses for statistics educators
- AP Statistics Summer Institute
- AP Statistics Exam Reader
- Other

Student Outcomes

In describing professional growth, a change in student outcomes often leads teachers to change the way they teach. For instance, a teacher may notice that after using more inference tasks in her classroom, that students are more likely to use data and evidence to support claims.

5. Using the description above as an example of student outcomes, do you believe that your participation in TSDI resulted in any significant changes in your students' outcomes? (Domain of Consequence)

- o Yes
- o No
- o Not sure
- o I did not participate in TSDI

6. Please describe any changes to your students' outcomes as a result of your participation in TSDI. (Domain of Consequence)

7. Using the description above as an example of student outcomes, do you believe that your participation in TSIR resulted in any significant changes in your students' outcomes? (Domain of Consequence)

- o Yes
- o No
- o Not sure
- o I did not participate in TSIR

8. Please describe any changes to your students' outcomes as a result of your participation in TSIR. (Domain of Consequence)

Community Influence

When describing professional growth, a change in one's values can also be seen on the influence that an individual has on changing another person's values. For example, after participating in TSDI, a community college instructor decides that engaging students in all four phases of the statistical investigation cycle is important for students to better understand statistics. She makes sure to include as many tasks in her own statistics course that uses all four phases as she can. After having good feedback from students, she then tells the rest of her department the positive results that engaging students in all four phases has had, so the rest of her department also adopts this practice. She has now made an influence on her community of practice.

9. Using the description above as an example of community influence, do you believe that your participation in TSDI resulted in you creating any influence on your community of practice? (Domain of Consequence)

- o Yes
- o No
- o Not sure
- o I did not participate in TSDI

10. Please describe the effect you believe you had on your community of practice as a result of your participation in TSDI. (Domain of Consequence)

11. Using the description above as an example of community influence, do you believe that your participation in TSIR resulted in you creating any influence on your community of practice? (Domain of Consequence)

- o Yes
- o No
- o Not sure
- o I did not participate in TSIR

12. Please describe the effect you believe you had on your community of practice as a result of your participation in TSIR. (Domain of Consequence)

Part 3. Further Research

Thank you for participating in this survey! Your participation is greatly appreciated and will hopefully help in research that can be used to create more opportunities for online learning.

If you wish to be entered into a drawing to win a $100 gift card, please enter your email address:

As part of this research study, I will also be collecting tasks from statistics educators and conducting follow-up interviews. Those that complete this survey, submit examples of 1 -2 current tasks you use, and participate in a follow-up interview will receive a **$50 gift card**. If you wish to be contacted to participate in further research, please indicate below:

- Yes, please contact me for potential participation in further research: email address
- No, I do not wish to participate in further research

Thank you for your time!

Appendix F – Interview Protocol

Hello. Thank you for agreeing to participate in this follow-up interview. The main goal of this interview is to ask you questions about your participation in TSDI and/or TSIR and learn what influence your participation in those courses may have had on your current professional life. Please note that you are free to answer or not answer any questions. If you would like to stop the interview at any time, please let me know. There are no right or wrong answers.

Do I have your consent to record this interview?

Questions/Prompts

1) Which course(s) did you participate in, Teaching Statistics through Data Investigations (TSDI) and/or Teaching Statistics through Inferential Reasoning (TSIR)? [Take note here of which course(s) the participant took to phrase the rest of the questions.]

    a) When did you take TSDI? TSIR?

2) I am interested in what motivated people to participate in these courses.

    a) How would you describe your professional role prior to enrolling in [TSDI/TSIR]? Has your role changed since your participation?

    b) Try to think back to when you initially enrolled in the [TSDI/TSIR], what prompted you to enroll? If you took a second course, why did you decide to enroll in [TSDI/TSIR]?

    c) What goals did you have when enrolling in [TSDI/TSIR]? The second course [TSDI/TSIR]?

    d) Did your goals change over the time of your participation in [TSDI/TSIR]?

3) I now want to ask you specific questions about your participation in the course.

    a) Thinking to the first course you enrolled in, [TSDI/TSIR]; how would you describe your engagement in the course? Did you visit every page, participate in every forum, complete microcredentials? Did you browse the materials and only view pages of interest?

i) Which parts of the course did you find the most engaging? The least engaging?

b) How would you describe your engagement in the second course, [TSDI/TSIR]? (if applicable)

i) Which parts of this course did you find most engaging? The least engaging?

c) The materials for either course was available to those that enrolled in the course after the course was complete. Did you access or use any of the materials for [TSDI/TSIR] after the course was closed?

4) What knowledge or skills do you think you gained from your participation in [TSDI/TSIR]?

a) For lurkers: Do you think that the knowledge/skills you learned may have been enhanced if your level of participation were different?

b) For highly active participants: Do you think that the knowledge/skills you gained from your participation in [TSDI/TSIR] was impacted by your high level of engagement?

5) I now want to ask you questions about how your professional life may have changed after your participation in [TSDI/TSIR].

a) **For statistics instructors**: Could you describe features and characteristics of statistics tasks you assigned to your students prior to your participation in [TSDI/TSIR]?

i) Did the tasks you use in your classes change after your participation? Describe features and characteristics of tasks you currently use in your statistics classes?

ii) Describe how you use the knowledge and skills you may have learned in [TSDI/TSIR] in your current teaching practice?

iii) Has the knowledge or skills you learned in [TSDI/TSIR] had an impact on your student outcomes? In what way?

iv) Has your participation in [TSDI/TSIR] made an influence on others in your professional community? For example, have you shown other instructors how to use a technology tool you used in class, or encouraged others to try to do more data investigations?

b) **For professional development coordinators:** Can you describe PD you facilitated for statistics educators prior to your participation in [TSDI/TSIR]?

i) How has the PD you facilitate changed after your participation? Can you describe a PD you find particularly impactful for statistics educators that you have recently facilitated?

ii) Describe how you use the knowledge and skills you may have learned in [TSDI/TSIR] in your current practice.

iii) Has the knowledge or skills you acquired in [TSDI/TSIR] had an impact on your PD outcomes? In what way?

iv) Has your participation in [TSDI/TSIR] made an influence on others in your professional community?

6) Can you describe any other ways you believe that your participation in [TSDI/TSIR] has influenced you professionally?

7) Is there anything else you would like to add or comment that has not been addressed?

Thank you for your time.

Appendix G – Goals chosen by participants in the enrollment survey

Goals chosen from enrollment survey by Unit 1 participants. Note: This total is more than the number of participants since there was an option to rank the top 3 goals.

Goal from enrollment survey	**Total**
Strengthen my understanding of how to engage students in statistical investigations	881
Improve my ability to use rich data sources to support investigations	478
Improve my ability to use dynamic tools to visualize and analyze data	386
Just browsing	22
Deepen my knowledge of the course topic(s)	425
Connect with peers/colleagues/ Exchange ideas and experiences with other educators	174
Collect resources and tools for my practice/Collect new resources or tools	666
Earn a certificate of accomplishment/renewal credits/Earn a certificate of completion	174
Collaborate on joint projects	35
Engage in fun and inspiring activities	341
Deepen my understanding of how students reason with data	498
Make changes to my professional practice	0
Experience learning in a MOOC-Ed	237

Appendix H – R Code for Topic Modeling Method 1, Unsupervised Learning Method

This document shows the steps used to perform LDA topic modeling on the merged posts from the introductory discussion forums in TSDI or TSIR. LDA is an unsupervised learning method.

```
library(readxl)
intro <- read_excel("~/Dissertation/Data/TopicModeling/TopicModelingbyPostID/
posts_merged.xlsx")
```

##Creating the DTM

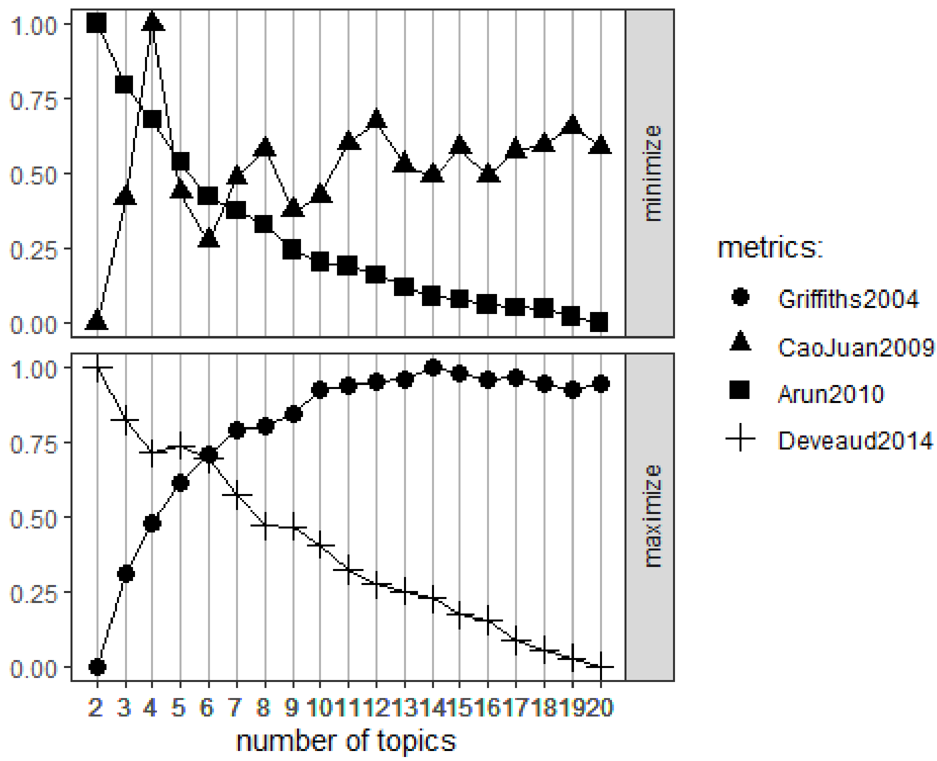
Steps to create a document term matrix for the posts above.

```
dtm <- CreateDtm(doc_vec = intro$posts_merged, # character vector of document
s
                 doc_names = intro$userid_bycourse, # document names
                 ngram_window = c(1, 2), # minimum and maximum n-gram length
                 stopword_vec = c(stopwords::stopwords("en"), # stopwords fro
m tm
                  stopwords::stopwords(source = "smart")), # this is the defa
ult value
                 lower = TRUE, # lowercase - this is the default value
                 remove_punctuation = TRUE, # punctuation - this is the defau
lt
                 remove_numbers = FALSE, # numbers - this is the default
                 verbose = FALSE, # Turn off status bar for this demo
                 cpus = 2, # default is all available cpus on the system
                 stem_lemma_function = function(x) SnowballC::wordStem(x, "po
rter"))
```

##Number of Topics using FindTopicNumbers

```
result <- FindTopicsNumber(
  dtm,
  topics = seq(from = 2, to = 20, by = 1),
  metrics = c("Griffiths2004","CaoJuan2009", "Arun2010", "Deveaud2014"),
  method = "Gibbs",
  control = list(seed = 77),
  mc.cores = 2L,
  verbose = TRUE
)

## fit models... done.
## calculate metrics:
##   Griffiths2004... done.
##   CaoJuan2009... done.
##   Arun2010... done.
##   Deveaud2014... done.
```

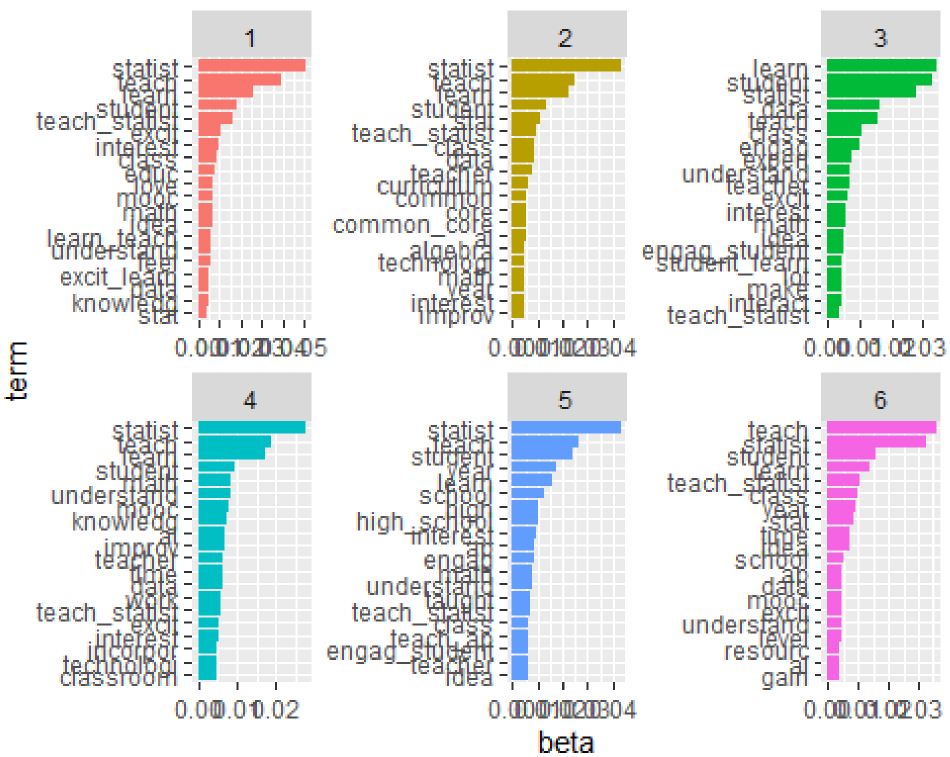
```
FindTopicsNumber_plot(result)
```



Fit a Latent Dirichlet Allocation model

```
# set a seed so that the output of the model is predictable
model <- LDA(dtm, k = 6, control = list(seed = 91))
#creates a matrix with topics
forum_topics <- tidy(model, matrix = "beta")
forum_topics

## # A tibble: 53,598 x 3
##    topic term             beta
##    <int> <chr>           <dbl>
##  1     1 101         3.67e-210
##  2     2 101         1.96e-207
##  3     3 101         8.82e-209
##  4     4 101         2.68e-187
##  5     5 101         2.30e-210
##  6     6 101         2.52e-  4
##  7     1 101_includ 3.15e-210
##  8     2 101_includ 8.02e-208
##  9     3 101_includ 8.21e-209
## 10     4 101_includ 5.70e-187
## # ... with 53,588 more rows

#ggplot visualization of topics with top 20 terms using beta matrix
```

```
library(ggplot2)
library(dplyr)

forum_top_terms <- forum_topics %>%
  group_by(topic) %>%
  top_n(20, beta) %>%
  ungroup() %>%
  arrange(topic, -beta)

forum_top_terms %>%
  mutate(term = reorder_within(term, beta, topic)) %>%
  ggplot(aes(term, beta, fill = factor(topic))) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free") +
  coord_flip() +
  scale_x_reordered()
```



The gamma value of the participants is the likelihood that a topic is associated with a participant. Only participants with a gamma > 0.5 were kept for analysis, meaning that a majority of the words belong to that topic.

```
#topics using gamma matrix, by participant instead

forum_participants <- tidy(model, matrix = "gamma")
forum_participants <- forum_participants %>% filter(gamma>0.5)
```

Appendix I – R Code for Topic Modeling Method 2, Semisupervised with Seeded Dictionary

This document describes the coding methods used for the Topic Modeling Method 1, an Unsupervised Learning approach.

```
introduction_posts <- read_excel("~/Dissertation/Data/TopicModeling/TopicMode
lingbyPostID/posts_merged.xlsx")
```

After importing the data, a data frame was made with the userid in one column and the posts as the second column.

```
dat <- data.frame(user = introduction_posts$userid_bycourse,
                  post = introduction_posts$posts_merged)
```

Ensure that the post column is a character vector

```
dat$post <- as.character(dat$post)

corp <- corpus(dat, docid_field = "user",
                    text_field = "post")
```

Use the data frame above to create a document feature matrix. In the DFM below, the first 10 rows and columns are previewed.

```
dfmt <- dfm(corp)

## Warning: 'dfm.corpus()' is deprecated. Use 'tokens()' first.

dfmt[1:10,1:10]

## Document-feature matrix of: 10 documents, 10 features (62.00% sparse) and
0 docvars.
##           features
## docs       as i get closer to graduation , am seeking enhance
##   10014_52  1 2   1      1  4          1 1  1       1       1
##   10040_40  0 2   0      0  2          0 1  2       0       0
##   10168_52  0 2   1      0  4          0 1  1       0       0
##   10168_76  0 0   1      0  1          0 0  0       0       0
##   10185_52  4 9   0      0  5          0 5  0       0       0
##   10204_52  0 2   0      0  2          0 0  1       0       0
## [ reached max_ndoc ... 4 more documents ]
```

The seeded dictionary was created and added in for the seeded dictionary function.

```
seeded_dict_short <- dictionary(list(engagingclass = c("engag*","excit*","app
eal*"),
                               confidence = c("confidence", "confident","buil
d*"),
```

```
                               repeater = c("back", "attempt", "last","second
"),
                               realdata = c("data", "real", "world"),
                               technology = c("technology", "calculator", "ap
plet","dynamic"),
                               pedagogy = c("approach", "pedagogical", "teach
*"),
                               #evidencebased =c("analyze", "evidence", "expl
anation"),
                               statsinvestigations = c("investigation", "hand
s-on", "experiment"),
                               studentsreasoning = c("student", "think*", "re
ason*"),
                               collaborate = c("share", "community", "collabo
rat*","discussion*","other*","interact*"),
                               libraryofresources = c("resources", "activitie
s", "library","gather*"),
                               preparing = c("common", "science", "curriculum
","class"),
                               professionalpractice = c("experience", "profes
sional", "practice","certificate"),
                               learnstatistics = c("content", "knowledge", "u
nderstanding","statistics"),
                               requirement = c("required", "requirement", "en
roll","renewal","credit")
))
```

The seeded dictionary created previously was used to perform seededlda function

```
library(seededlda)

##
## Attaching package: 'seededlda'

## The following objects are masked from 'package:topicmodels':
##
##     terms, topics

## The following object is masked from 'package:stats':
##
##     terms

slda <- textmodel_seededlda(dfmt,
                            seeded_dict_short,
                            valuetype = c("glob", "regex", "fixed"),
                            case_insensitive = FALSE,
                            residual = FALSE,
                            weight = 0.01,
                            max_iter = 2000,
                            alpha = NULL,
```

```
                                beta = NULL,
                                verbose = quanteda_options("verbose"))
```

The following are the steps done to create a table with the topic assigned to each user.

```
#this shows the top terms per the topic modeling package
)
terms <- terms(slda)

#defines topics based on seeded topic modeling
topic <- topics(slda)

#assigns names to the topic, in this case the userid_bycourse
names(topic) <- docnames(dfmt)

seeded_ldatopics_byuser <- data.frame(topic, slda$alpha)

write.table(seeded_ldatopics_byuser, "~/dissertation/seededlda_results052321.
csv")
```

Appendix J - R code for Motivation and Engagement Cluster Analysis

K-means clustering was used to cluster the participants of TSDI and TSIR into groups based on motivation. A motivation matrix was created that had 4 variables; topic modeling goal, goal1, goal2 and goal3. Each row of the matrix was a participant, and each column was one of those four variables.

The `cluster` package has the kmeans function that will be used.

The motivation matrix was built off of a master matrix that included all motivation and engagement data. Any cells that had NA had to be coerced to a 0 for the kmeans function to work.

```
library(readxl)
engagement_motivation_matrix050521 <- read_excel("C:/Users/Heather/Documents/
Dissertation/Data/Engagement/engagement_motivation_matrix050521.xlsx")
motivation <- engagement_motivation_matrix050521
userid <- engagement_motivation_matrix050521$`Userid Bycourse`
motivation <- data.frame(motivation[,2:5])
motivation[is.na(motivation)] <- 0
```

The `Nbclust` package was used to determine the ideal number of clusters. The NbClust function runs 30 different indices to determine the "ideal" number of clusters. The majority rule states that the number of clusters that should be used is the one that has that number appear the most often.

According to the majority rule, the best number of clusters is 3.

Using this, K-means clustering for the motivation data set was performed as follows. A seed was set for reproducibility.

The `withinss` is a measure of the sum of squares within the clusters. As this number starts to even out, the withinss is minimized. 'nstart' is the number of times a different center is chosen as a means to identify clusters. I started with n = 20, then tested up to 100. The `withinss` did not change past 20.

```
set.seed(2)
km.out=kmeans(motivation,3,nstart=20)
km.out$withinss

## [1] 15367.37 18285.59 12071.78

#withinss for each cluster with nstart = 20; 12071.78 15367.37 18285.59
```

A table was then created binding the userid_by course to the identified clusters to be used for later analysis.

```
kmeans_table <- cbind(userid,kmeans_motivation_cluster = km.out$cluster,motiv
ation)
```

The same procedures as above were used for the engagement data.

```
engagement <- data.frame(engagement_motivation_matrix050521[,6:88])
engagement[is.na(engagement)]<-0
```

According to the majority rule, the best number of clusters is 2 or 3

```
set.seed(2)
km.engage = kmeans(engagement,3,nstart=200)
km.engage$withinss

## [1] 24043157 26999326 39679946

kmeans_engage_table <- cbind(userid,kmeans_cluster=km.engage$cluster,engageme
nt)
```

Appendix K – Variables Used for Cluster Analysis

The following is a list of variables that were used for cluster analysis. Topic_modeling_goal, goal1, goal2, and goal3 were used for the motivation cluster analysis. The remaining were used for the engagement cluster analysis.

Motivation factors

- **topic_modeling_goal** - Goal determined by Method 3 of topic modeling analysis
- **goal1** – first goal indicated on enrollment survey
- **goal2 –** second goal indicated on enrollment survey
- **goal3 –** third goal indicated on enrollment survey

Pages in modules – the following are a list of page types that participants could click on in the course

- **attempt** – attempt at an embedded quiz
- **attempt_summary** – view of the score on an embedded quiz
- **chapter** – chapter within a lesson
- **content_page** - a page that has content on it, textual, videos, quizzes, etc.
- **course_module** – any click on a page in a module is counted as a click on a course module, which are the units of each module
- **course_module_completion** - viewing the page that indicates a course module is complete
- **discussion** – open a discussion page, to view or post
- **lesson post** – post within a lesson that requires a discussion
- **questionnairre** – unit feedback survey
- **resource** – opening a resource page
- **response –** response to a discussion
- **transcript** – opening a transcript for a video
- **video** – video embedded on a webpage

Units in each course – the following is a list of units that participants could access. Each hit was recorded for which unit the resource or page a participant was viewing.

- **Guides to Support Professional Development –** a unit in sections of TSDI that was used for those participating in PLCs
- **Orientation** – TSDI orientation Unit
- **TSDI Unit 1: Considering the Possibilities of Teaching Statistics with Data**
- **TSDI Unit 2: Engaging in Statistics**

- **TSDI Unit 3: Introducing Levels of Statistical Sophistication**
- **TSDI Unit 4: Delving Deeper into the Investigation Cycle**
- **TSDI Unit 5: Putting It All Together**
- **TSDI Participate With A Project –** some sections of TSDI offered a chance to submit a project and participate in discussions about the project
- **TSIR Unit 0: Orientation and Review of SASI Framework**
- **TSIR Unit 1: What Is Inferential Reasoning?**
- **TSIR Unit 2: Inferential Reasoning With Comparing Groups**
- **TSIR Unit 3: Inferential Reasoning Between Samples and Population**
- **TSIR Unit 4: Inferential Reasoning With Competing Models**
- **TSIR Unit 5: Making Inferential Reasoning Essential in Your Practice**

Weekly hits – hits were recorded by Weeks during the course, the during total. The weeks for viewing the course after it closed were recorded in 8 week increments. For example Post1_8 indicates the number of hits a participant had in the first 8 weeks after a course closed.

- **Pretotal**
- **Week1 Week2 Week3 Wee4 Week5 Week6 Week7 Week8 Week9 Week10 Week11 Week12 Week13 Week14 Week15 Week16 Week17 Week18 Week19 Week200 Week21 Week22 Week23 DuringTotal**
- **Post1_8 Post9_16 Post17_24 Post25_32 Post33_40 Post41_48 Post49_56 Post57_64 Post65_72 Post73_80 Post81_88 Post89_94 PostTotal**

Discussion Forum Hits – discussion hits were recorded

- **total_discussionposts**
- **total_replies**
- **total_thread_starts**
- **TSDI_Orientation_posts**
- **TSDI_Unit1_posts**
- **TSDI_Unit2_posts**
- **TSDI_Unit3_posts**
- **TSDI_Unit4_posts**
- **TSDI_Unit5_posts**
- **TSDI_participatewithaproject_forum**
- **TSIR_OrientationPosts**
- **TSIR_Unit1_posts**
- **TSIR_Unit2_posts**
- **TSIR_Unit3_posts**
- **TSIR_Unit4_posts**
- **TSIR_Unit5_posts**