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Lurking and participation in the virtual classroom: The effects of gender, race, and age among graduate students in computer science

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ABSTRACT

Fully-online graduate degree programs are on the rise, generating new questions about how we conceptualize and measure student participation in the virtual classroom. To date, most studies examine participation patterns in single online and/or hybrid courses and do not take into account the demographic characteristics of online students. We develop and test hypotheses that address demographic differences in the nature and intensity of graduate student participation in online-only classrooms for a large degree program in computer science. This work is distinctive because it addresses participation across several classes and across multiple semesters. We select the Piazza forum because it is the required communication mechanism in the program that is the subject of our study. We extract Piazza discussion board activity logs from a sample of 1914 online computer science graduate students, specifically the numerical data indicating the type of access to Piazza students used. We distinguish between active (contributions), passive (viewership) participation and lurking behavior. Given the nature of the dependent variables of interest, we employ different forms of regression analysis. We use logistic regression to address the likelihood of non-participation in the online forum. We then use negative binomial regression to examine the intensity of passive and active engagement, and ordinary least squares regression to examine lurking behavior. We find that the intensity of participation varies by different demographic characteristics, including by age and by race/ethnicity, but not by gender. Our study also shows a notable impact of class size, where increasing class size is associated with decreasing levels of active participation and increasing lurking behavior.

1. Introduction

What drives graduate students to participate in an online classroom, and what does this participation entail? As online graduate degree offerings expand, researchers must grapple with challenges in both conceptualizing and measuring various aspects of the student experience and contextualizing it to the age and career stage of graduate students. Developing a better idea of how students engage can inform not only an understanding of online learning behaviors, but also the shifting ways in which students and faculty engage in a virtual educational world.

Online participation, often measured as the interaction *among* students and *between* students and instructors (Hrastinski, 2008), allows students to develop critical thinking skills, reflect on course material, and improve cognitive processing capabilities (Bliss & Lawrence, 2009). Further, recent work has shown that peer support in the online environment has a positive relationship with the resources and social connections that students have in this setting, and that instructors play a key role in facilitating these connections (Cocquyt, Zhu, Diep, De Greef, & Vanwing, 2019). In comparison to the traditional classroom environment, some have argued that

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online discussion boards may allow for even deeper learning experiences and the engagement of a broader and more diverse student body (Bliss & Lawrence, 2009; Cheng, Paré; Collimore, & Joordens, 2011; Fredericksen, Picket, Shea, Pelz, & Swan, 2000).

The goal of this study is to explore the nature and intensity of student participation in graduate-level, online-only classrooms and how this participation varies among demographic groups. In studies of online courses, participation in virtual discussion boards constitutes one important predictor of student outcomes, including perceived learning (Jiang & Ting, 1999), course performance (Cheng, Paré, Collimore, & Joordens, 2011; Picciano, 2002), and persistence (Morris, Finnegan, & Wu, 2005). However, few studies exist at the intersection of a highly technical discipline and an adult population pursuing a graduate degree.

Our focus is in the discipline of computer science, where about half of US master's degrees are earned by international students, few racial/ethnic minorities are evident (3%Hispanic and 6%black), and most graduates (70%) are men (National Science Foundation, 2019). In many science, technology, engineering, and mathematics (STEM) disciplines, underrepresented groups have been shown to experience chilly climates and negative stereotypical judgments about their math abilities, contributing to low self-efficacy beliefs, anxiety, and timidity (Cheryan, Master, & Meltzoff, 2015; Du, Ge, & Xu, 2015). With computer-mediated communication, there is speculation that online education may reduce or remove many social and contextual cues and, thereby, create an environment that is gender and race neutral and inclusive (Gunn, McSporran, Macleod, & French, 2003; Kollock & Smith, 1996). This can be especially impactful in disciplines where stark demographic differences exist, and social exclusion can have effects on interest, and the pursuit of career opportunities, in the field.

With a growing literature on online learning, increased attention to the importance of examining various demographic attributes in such studies is critical (Money & Dean, 2019). Yet, most studies of adult learners in the online space are more remedial in nature (Money & Dean, 2019), which may not be translatable to more advanced populations of students. While some studies have identified an online gender participation gap, there is disagreement regarding its size and direction (Barrett & Lally, 1999; Herring, 2000; McSporran & Young, 2001; Rovai & Baker, 2005; Sankar, Gilmartin, & Sobel, 2015). Again, it is not clear whether this gap would be evident among working adults seeking an advanced degree. We seek to address these gaps and improve the understanding of online participation patterns among different demographic groups in a STEM discipline by examining the following research questions:

1. To what extent do graduate students participate in online learning discussion boards?
2. For those who participate at all, what are the patterns of their engagement?
3. How does the type and intensity of online participation vary by student demographics and class setting?

We address the questions above using data from a required online discussion board for several classes in a fully-online master's degree program in computer science. Data include 18% of courses in the two years of data we examined. The required modality enables us to examine student behavior in several different classes within a single institutional setting (and related norms, student body and so on). Our objectives are to a) identify the different forms of class participation in the online context and examine how that varies by individual characteristics, as well as class size, and b) to distinguish between active and passive participation, as well as to capture the intensity of participation.

Our study is somewhat exploratory in nature because participation in online settings, and particularly advanced degree settings, is neither well explored nor understood. Thus, we hope that our work contributes to the growing body of research in this realm in a few ways. First, as we note in our discussion, online graduate degrees are increasing, yet the body of empirical research on these programs is relatively small. Our research setting is a high-enrollment online computer science graduate degree program offered by a major research university in the United States. Most studies of online learning and related student experience investigate participation in single online or hybrid *courses* (Bainbridge et al., 2015; Bercovitz & Feldman, 2007; Song & McNary, 2011; Weidlich & Bastiaens, 2019; Young & McSporran, 2004) while research on online *degree programs* (Allen & Seaman, 2017), and particularly *graduate programs,* is rare, despite their growing significance in the United States. Second, our data comes from the discipline of computer science, where participation and advancement of underrepresented groups remains a challenge. Third, we examine a student body that demonstrates considerable age diversity, including a large number of mid-career, working adults. Given that most studies of online learner adults over the age of 25 are pursuing initial degrees and have a number of readiness limitations (Money & Dean, 2019), our examination of highly-qualified adult students examines a population not often found in this literature.

2. Literature review

2.1. Conceptualizing online participation

In a traditional classroom setting, participation can be understood as an active student engagement process that involves class preparation, attendance, contribution to discussions, group skills, and communication skills (Dancer & Kamvounias, 2005). Verbal contributions such as asking and answering questions, providing comments, and giving constructive feedback are equally important as nonverbal contributions such as allowing classmates to speak and listening to discussions (Schultz, 2009). Instructors play an important, but not the only role, in facilitating and nurturing student engagement (Mulryan-Kyne, 2010). Classroom attributes, most importantly class size and climate, also influence the amount and intensity of student participation (Crawford & MacLeod, 1990; Fassinger, 2000). More specifically, chilly and unsupportive classroom environments may suppress participation (Crawford & MacLeod, 1990), while larger classes decrease opportunities of interaction with professors and peers (Beattie & Thiele, 2016; Fassinger, 2000). Assessing the level of student engagement in this setting occurs against a background of multiple visual and verbal cues. Instructors can easily determine attendance, observe in real-time if students are paying attention (e.g., eye-contact with the instructor and other students, note-taking), and evaluate the contributions to discussions (e.g., understanding of the material, expressing own ideas, use of vocabulary).

Examining participation in the online classroom presents certain challenges. The virtual classroom introduces a transactional distance (Falloon, 2011; Moore, 1991) by physically separating students and instructors and offers a different learning environment that is largely characterized by discussion boards and video streaming, generating questions on how we understand student participation – both theoretically and empirically. Hrastinski (2008) has characterized online participation as a multi-level process in which course-site access constitutes the first level followed by contributing to discussions and reading contributions of others. Only a small number of studies, however, have captured how often students access course sites and learning materials (Caspi, Chajut, & Saporta, 2008; Macfadyen & Dawson, 2010; You, 2016). Student engagement in online discussions is seen as a much more important component of participation, motivated by theoretical considerations that communication in discussion boards and interaction between students determine learning outcomes (Bliss & Lawrence, 2009; Cheng et al., 2011; Fredericksen et al., 2000; Morris et al., 2005).

Engaging in online discussions is predominantly associated with making text-based contributions such as asking questions or replying to posts, commonly referred to as *active participation* (Dennen, 2008; Hrastinski, 2008; Kim, 2013). Whether engagement also includes less visible forms such as reading other students' posts, frequently termed passive participation or *lurking*, has not been without debate. Some studies have portrayed lurkers as nonparticipants and free-riders who benefit from the information contributed by other students without generating any value themselves, highlighting that lurking undermines the principle of sharing knowledge that online communities depend and thrive on (Kollock & Smith, 1996; Morris & Ogan, 1996; Van Mierlo, 2014). Other studies object, arguing that lurkers are *participants* since they are not absent from the virtual classroom but visit the course site and observe discussions (Edelmann, 2013). As such, lurking reflects a different learning style, where students choose to participate in a less formal, quieter way, yet may still engage deeply with learning materials and discussions (Dennen, 2008; Hrastinski, 2009; Nonnecke; Preece, 2000; Teo; Johri, & Lohani, 2017; Xie, Yu, & Bradshaw, 2014).

2.2. Determinants of online participation

Understanding student engagement in online learning requires identifying the factors that influence participation. However, no empirically-validated model for online participation exists and we are only beginning to understand the drivers and inhibitors of active and passive participation. Prior work, however, suggests three important factors that shape whether and how students participate online: individual characteristics, online community characteristics, and technological aspects.

Individual characteristics: Self-efficacy, which reflects the student's confidence in their ability to perform specific tasks successfully, appears to be a particularly important individual characteristic influencing online behavior (Amichai-Hamburger et al., 2016; Gunawardena, Linder-VanBerschot, LaPointe, & Rao, 2010; Pituch & Lee, 2006; Shen, Cho, Tsai, & Marra, 2013; Sun, Rau, & Ma, 2014). Generally, students with high self-efficacy are expected to participate more actively in the virtual classroom (Tedjamulia, Dean, Olsen, & Albrecht, 2005). However, predicting participation based on self-efficacy is highly complex given that a successful online learning experience requires students to have different self-efficacies capturing technological, learning, and social-interactive dimensions (Cho & Jonassen, 2009; Shen et al., 2013). Student personality is another factor that has been shown to influence online behavior. Yet, we lack clarity as to whether a particular personality trait such as extroversion, neuroticism, or conscientiousness determines the intensity of active or passive participation (Amichai-Hamburger et al., 2016; Balaji & Chakrabarti, 2010; Cullen & Morse, 2011; Malinen, 2015). Finally, student self-identified needs appear to influence participation patterns. Students with greater social and achievement needs may participate more actively while students with greater informational needs may be satisfied with lurking (Nonnecke & Preece, 2000; Sun et al., 2014; Tedjamulia et al., 2005).

Online community characteristics: Effective online learning hinges on the development of a community, which is characterized by trust, shared values, and a sense of belonging (Rovai, 2002; Rovai & Ponton, 2005). Studies suggest that participation in online discussions is both driving and benefitting from a strong sense of community among students (Balaji & Chakrabarti, 2010; Hrastinski, 2009). Students who feel that they belong in an online community contribute more (Sun et al., 2014) and, conversely, active participants experience a greater sense of belonging in the online community than lurkers (Preece, Nonnecke, & Andrews, 2004). Recent evidence suggests that sense of belonging and trust alone do not determine participation in online discussion boards, but that students have to feel that their efforts and contributions are being reciprocated (Diep, Cocquyt, Zhu, & Vanwing, 2016).

Technological aspects: The technological environment may shape student participation patterns. The design of the online platform interface determines how students perceive the usefulness and ease-of-use of the system, which, in turn, influence their satisfaction and comfort with the platform (Amichai-Hamburger et al., 2016; Beaudoin, 2002; Pituch & Lee, 2006; Vonderwell & Zachariah, 2005). How easy or difficult students find it to contribute to discussions and interact with others depends on the types of collaborative features that the platform offers, its functionality, and the visual organization of the discussion board overall (Vonderwell & Zachariah, 2005). Also, students perceive a platform easier to use as they take more online classes and gain more experience with online learning systems (Arbaugh, 2004). Evidence suggests that higher perceived usability and usefulness is linked to higher active participation rates (Tedjamulia et al., 2005; Vonderwell & Zachariah, 2005) while lurking may be attributed to a lack of usability and technical difficulties with the platform (Nonnecke & Preece, 2000; Preece et al., 2004). However, similarly to studies in traditional classroom settings, group or class size appears to be an important confounding factor. Discussion groups with large numbers of students are correlated with high volumes of communication, which can lead to information overload and may cause students to decrease their level of active and passive participation as the number of postings increases (Jones, Ravid, & Rafaeli, 2004; Kim, 2013).

2.3. Demographics and online participation in STEM

Much of the online participation research to date has focused on examining the relationship between student participation in online discussion boards and learning outcomes (Cheng et al., 2011; Goggins & Xing, 2016; Koprinska, Stretton, & Yacef, 2015; Ramos & Yudko, 2008; Wei, Peng, & Chou, 2015). Few studies take into account the demographic characteristics of online students and those that do contradict each other in their findings of whether and how participation varies with respect to gender, race/ethnicity, and age. Inconclusive empirical findings may be explained by the inconsistency in participation measurement, along with the substantial diversity of research settings and the potential of disciplinary effects (Arbaugh, 2005). This is a core focus of our study. Knowing the factors that influence online participation may help us to predict how different demographic groups engage in online discussions in a STEM discipline.

Gender: STEM disciplines have traditionally been male-dominated, with computer science having one of the lowest proportions of female degree recipients among STEM disciplines (National Science Foundation, 2019). Studies show that one factor contributing to the persistent underrepresentation of women in STEM is the stereotypical environment that perpetuates the image of a geeky, nerdy culture in which women do not fit (Master, Cheryan, & Meltzoff, 2016). Stereotypical judgments can lower women's self-efficacy and increase self-blame in situations of failure (Koch, Müller, & Sieverding, 2008). Stereotypes have also been linked to undermining women's sense of belonging in the computer science field and classroom (Cheryan, Plaut, Davies, & Steele, 2009). From past studies, we know that the unwelcoming, "chilly" climate that female science students experience in the traditional classroom is equally prevalent in online environments (Caspi et al., 2008; Cheryan, Meltzoff, & Kim, 2011; Guiller & Durndell, 2006; Herring, 2000; Yates, 2001). For example, online discussion boards include linguistic cues that expose gender anonymity (Guiller & Durndell, 2007). However, how those aspects translate into participation patterns is not known. Very few studies investigate how online participation varies by gender and, to the extent they do, are conducted in non-technical disciplines. Two studies on student participation in an online computing course provide evidence that men have higher online technology self-efficacy than women, but women show higher rates of active and passive participation than men (McSporran & Young, 2001; Yukselturk & Top, 2013). More research is needed to understand how online participation patterns vary among men and women. The evidence on women's low self-efficacy beliefs and a low sense of belonging in computer science would suggest that ***female students participate less actively in online discussion forums than men (hypothesis 1).***

Race and Ethnicity: Blacks and Hispanics continue to be underrepresented among STEM degree holders (National Science Foundation, 2019). Similar to women, Blacks and Hispanics in STEM disciplines tend to lack peer relationships in college and may, therefore, feel excluded and like they do not belong (Litzler, Samuelson, & Lorah, 2014). Whether racial/ethnic minority students also demonstrate lower levels of self-efficacy and STEM confidence than their White and Asian peers is contested (Litzler et al., 2014). Yet again, the question is whether research findings from the traditional college environment can be generalized to the online learning environment. Rovai and Ponton (2005) argue that racial bias and stereotyping exist in traditional and virtual classrooms alike. In their study on online graduate students, Blacks felt more excluded from the social and learning communities and, thus, participated less in online discussions by posting fewer messages. From some online learning studies we know that female Black (Du et al., 2015), Hispanic, and Native American (Ke & Kwak, 2013) students may feel more reserved and intimidated in online discussions than their White counterparts, which may lead to lower active participation rates. With respect to other racial groups such as Asians, who are overrepresented among STEM degree recipients, we know even less about how they interact in an online learning environment. Based on theoretical considerations and findings that underrepresented minorities report a lower sense of belonging, we expect that ***underrepresented minority students participate in online discussion forums less actively than their peers (hypothesis 2).***

Age: There is considerable age diversity among online learners, including younger students who are well-versed in online social activities, and working adults with full-time jobs and families (Ke & Kwak, 2013; Yukselturk & Top, 2013). Studies suggest that older adults are more self-directed learners than their younger peers and, therefore fare better in the online learning environment. The argument is that asynchronous online courses facilitate self-directed and independent learning styles by providing more flexibility in scheduling their learning around work and family responsibilities (Bourdeaux & Schoenack, 2016; Yoo & Huang, 2013). In addition, older online students appear to be more intrinsically motivated to learn than younger students (McSporran & Young, 2001; Yoo & Huang, 2013). Studies comparing online students across academic levels mirror these findings by stating that undergraduate students are more peer-driven while graduate students are more motivated and self-directed (Arbaugh, 2010; Artino & Stephens, 2009; Croxton, 2014). Whether and how differences in individual characteristics among different age groups predict online participation in discussion boards is not well understood. Ke & Kwak. (2013) study is one of the few that examines online participation by age, finding that older students spend more time online with writing and reading posts than their younger peers. In contrast, a recent study by Diep et al., 2016) finds that age has no effect on online participation. Finally, there is a counter-argument that older adults would be likely to participate less, since they have lower levels of Internet self-efficacy and have difficulties using online tools due to weaker cognitive abilities and less experience interacting online (Chu, 2010). However, technological or Internet self-efficacy may be of less concern in STEM disciplines, and particularly computer science, where we would expect students to have had significant exposure to information and communication technology. In line with the argument that older students are more self-directed and motivated, we expect that ***older students participate more, both actively and passively, than their younger peers (hypothesis 3).***

Citizenship: Finally, examining participation patterns in a STEM discipline that is highly populated by international students raises questions of potential cross-cultural differences and participation patterns that are possibly attributable to different levels of English language proficiency and/or other cultural effects. In a study of Chinese graduate students taking online courses at a Canadian university, Zhao and McDougall (2008) hypothesized that Chinese students have a strong sense of achievement and may contribute more online if their participation is assessed and graded. In a comparative analysis of online students at US, Chinese, and South Korean universities, Wang (2007) found that Chinese and Korean students' motivation to participate in online discussions was mainly influenced by course requirements. Others suggest that students from Asian countries are more accustomed to structured, lecture-centered styles and may, therefore, face difficulties adapting to inductive, discussion-based learning formats, which could negatively impact active participation (Liu, Liu, Lee, & Magjuka, 2010). As a result, students from Asian countries may prefer not to voice opinions and to contribute less to online discussions to avoid conflicts (Lim, 2004; Zhao & McDougall, 2008). Finally, some studies have examined how language proficiency influences participation among non-native students, but it remains unclear whether limited English language skills increase (Biesenbach-Lucas, 2003) or decrease (Gunawardena et al., 2001; Liu et al., 2010) active participation. Cultural and language issues in online participation are not well understood and represent an important area to empirically examine.

3. Material and methods

3.1. Research setting

Data for this study come from the Georgia Institute of Technology's Online Master of Science in Computer Science (OMSCS) degree program. The research team is not affiliated with the program and is conducting independent research on the experiences and outcomes of its students. Launched in 2014, OMSCS has identical requirements to and confers the same degree as the Georgia Institute of Technology's 8th-ranked (US News & World Report, 2018) residential Computer Science Master's program, but offered at low-cost (under $7000 total tuition) in a fully-online, asynchronous format ("OMSCS FAQ," 2018). OMSCS offers twenty-nine courses and four specializations: Computational Perception & Robotics, Computing Systems, Interactive Intelligence, and Machine Learning. With over 6000 currently enrolled students and a growing alumni population, OMSCS makes up a discernible portion of all US computer science master's students. (31,552 master's degrees in computer science were awarded nationally in 2015 (National Science Board, 2018).)

Our study is based on the participation activity within an online discussion board, required in all OMSCS courses. Relevant to our study, OMSCS instructors and their teaching assistants exclusively use ***Piazza*** (Piazza.com) as a platform to support communication with and among students. In contrast to learning management systems such as Blackboard and Canvas, Piazza is an add-on tool for these types of platforms. It was specifically designed for the purpose of facilitating class discussions and peer learning by providing a forum where students can ask questions, respond to each other, and receive instructor/TA answers to their queries. Piazza reports that its forums are a broadly utilized tool, having been used by 50,000 professors in over 2000 universities across 90 countries (Piazza Technologies, 2019). Due to the fully-online nature of OMSCS, Piazza constitutes the virtual classroom and provides the central hub for students to communicate with their peers, professors, and teaching assistants, which, in turn, creates a unique set of push and pull factors for online participation. Because it is a required platform, it also allows us to examine participation across different courses.

In our study of online participation, a fully-online, advanced degree program provides several advantages over studies of massive open online courses (MOOCs) and single-course online classes. MOOCs are often inconsistent in their evaluation procedures, leading to varied levels of engagement by students with course material (Banks & Meinert, 2016; Zhu, Sari, & Lee, 2018). In contrast to a fully-online degree program, single-course online classes (offered as part of a traditional degree program) may include students who are not socialized or committed to the online education environment. Since the vast majority of studies of online class discussions have been the MOOC or single course setting (Hrastinski, 2008; Li & Baker, 2018; Weidlich & Bastiaens, 2019; Zhu et al., 2018), the OMSCS degree program setting provides a significant advantage in the study of online participation. Because OMSCS students exclusively take courses online without ever attending the institution's physical campus, they have a limited environment in which to interact, distinguishing them from other online student populations who occasionally take hybrid or fully-online courses. Further, we have an opportunity to gain a more nuanced understanding of the nature of different types of participation in online communities and how they interrelate. Our unique observational and demographic dataset allows us to ask new questions from prior studies of online participation, which have primarily studied active participation at the individual level with limited demographic data (Hrastinski, 2008). In this study, we are also able to measure passive participation (Lee, Chen, & Jiang, 2006), whose relationship to active participation has often been less intensely examined in prior studies (Edelmann, 2013; Lee, Carter-Wells, Glaeser; Ivers, & Street, 2006; Sun et al., 2014).

3.2. Piazza and student data

With the approval of Georgia Tech's Institutional Review Board (IRB), we obtained activity logs from Piazza Technologies for a set of OMSCS courses. These logs represent the comprehensive record of all discussion board activity in a given course over a semester from students, TAs, and professors, stored as a single Python file. Piazza participation data were then merged with student

Table 1
Piazza course sample composition.

Semester	Courses		Students	
	n	Percentage	n	Percentage
Fall 2016	4	16	760	15
Spring 2017	4	17	654	11
Fall 2017	5	21	1449	19

demographic data obtained from the Institute, including students' gender, race/ethnicity, age, and citizenship status. After data cleaning (removal of instructors and teaching assistants, and students enrolled in multiple courses within our selection), we obtained a final dataset of Piazza enrollment and participation data for 1914 students.

A purposive sample of thirteen course sections across six different OMSCS courses held in fall 2016, spring 2017, and fall 2017 was identified for this study. The sample includes 4–5 courses from each semester, representing between 16% and 21% of individual courses and 11%–19% of program participation by students (Table 1). Courses were selected to represent a range of OMSCS's offerings, featuring both foundational courses and electives. Topics included high-performance computing, computational photography, computer vision, database systems design, knowledge-based artificial intelligence, and artificial intelligence for robots. This exploratory sample was drawn rather than the full set of courses in order to determine whether we could differentiate participation behavior as expected. This then provides a foundation for future longitudinal studies.

The specific data were drawn from the records Piazza maintains for each course. Students are required to use Piazza as the communication platform for the course. The platform automatically records the range of student activities for each individual within the platform on an on-going basis over the duration of the course (specific variables are discussed below). In order to view any course content, the student is required to log on the discussion board and 'click' on any type of contribution to read it, although they may see a partial preview without it registering. Piazza also records when students make a post or comment on an existing post, thus providing data on both active participation in the discussion forum (posting and other forms of content creation) and passive participation (viewing the posts of others). The recording of these different student actions enables us to differentiate between different types of participation, as described in the variable discussion below.

3.3. Variables

From Piazza participation and student demographic data, we operationalize our key constructs as follows. Piazza data are generally a binary or count variable. Demographics are binary variables. Variable distributions and frequencies are provided later in this paper.

3.3.1. Dependent variables: participation

Online Participation vs Nonparticipation. Measuring participation in an online course is challenging, as we have noted in our literature review. However, the required nature of Piazza in the OMSCS courses enables us to capture participation because of the limited mechanism that students have to interact with the professor, TAs, and one another within the context of the course. We measure whether students are participating at all using a binary variable indicating whether students enrolled in OMSCS courses viewed or commented at least one time on their section's Piazza forum (Table 2).

Active and Passive Participation Intensity. We recognize that participation is more than a binary concept, and, therefore, we also measure intensity of participation to differentiate lower and higher levels of student engagement. Active participation is a count of the number of times students posted new threads on Piazza or responded to existing threads. Conversely, passive participation is a count of the number of times students viewed Piazza forum posts over the course of the semester.

Lurking Behavior. Technical challenges, lack of theory, and the unavailability of data pose significant challenges to the study of lurking and viewership (or "passive participation") on the individual level in online communities (Edelmann, 2013; Sun et al., 2014). Prior studies of lurking have struggled to effectively measure or even consistently define lurking in online message-board settings (Hrastinski, 2008, 2009), typically relying on simple ratios or arbitrary cutoffs (Edelmann, 2013; Sun et al., 2014). As an alternative, we conceptualize lurking as a continuous construct, defining it as a normalized ratio between passive and active participation. We base our 'Lurking Index' on the E/I Index (Krackhardt & Stern, 1986), often used in social network studies. The E/I Index formula (A – B/A + B) is a strong choice for this application because it is less sensitive to small fluctuations and total participation than simple ratios. Values range between negative one (active participation only) and positive one (passive participation only) in our formulation: (Views – Posts/Views + Posts). For example, an "extreme lurker" who views the message board but never posts would have a Lurking Index of '1', a student who posts but never views any content (including responses to their own posts) would have an index of '-1', and values between -1 and $+1$ illustrate the relative proportion of these activities (and where '0' would represent an equal balance of the two behaviors).

Table 2
Variables.

Theoretical Concept	Dependent Variable Operationalization	Description of Variable
Non-Participation	Non-participant on Piazza	A binary variable coded '0′ for students who viewed and/or posted on the class message board at least once over the course and coded '1′ for students the neither viewed nor posted.
Passive Participation Intensity	Number of Views of Piazza Posts	Total number of views for the student during the course
Active Participation Intensity	Number of Posts on Piazza	Total number of posts for the student during the course
Lurking Behavior	Extreme Lurking	A binary variable coded '0′ for students who have posted at least once and '1′ for those that have viewed at least once, but never posted.
	Lurking Index	Index indicating the relative intensity of passive participation to active participation by a student, using the E/I Index formula: (Views - Posts/Views + Posts)

3.3.2. Class section size

There are significant disagreements in the literature about the impact of class sizes on student participation in online discussions (Kim, 2013; Rovai, 2007; Sun et al., 2014). However, given the attention of prior studies in traditional classrooms on the importance of class size for participation, we include the size of OMSCS class sections in our regression models. While most scholars agree that there is a linear effect of class size on lurking behavior in online course settings (Jones et al., 2004; Kim, 2013), others suggest that a flat, threshold effect occurs when a course reaches as few as 20–30 students (Rovai, 2007). While larger classes tend to have more user-generated content for students to view and interact with overall, they may have less of a sense of community and the larger volume of posts may cause information overload, resulting in mixed experiences. We measure class size using the actual course enrollment count. Note that we tested models with linear class size controls (class size count), class size tiers, and no class size controls; finding similar results. The models with linear class size controls had the greatest predictive power and we present those in the results section.

3.3.3. Demographics

We include several demographic variables in our models, including gender, race/ethnicity, age, and citizenship, given that student experiences often vary across these groups. Each of these characteristics (except age) are coded as binary variables (Table 3). Only a small portion (15%) of our sample are female, equivalent to the proportion of women enrolled in OMSCS, which is overall fewer than the 30% of female students graduating with a computer science master's degree nationwide in 2015 (National Science Board, 2018). Mean student age is 33 years old, ranging widely (from 19 to 64 years). A plurality of students in our sample (45%) are White, which is somewhat unusual in computer science, where Asians typically make up the majority (National Science Board, 2018). However, Whites and Asians together make up most of our sample (85%). Underrepresented minorities in STEM (Black and Hispanic students) make up 12%, with the remainder of students (3%) being from a multiracial background. The majority of students are US citizens (61%), with an additional 8% being US permanent residents (i.e. green card holders).

In terms of the distribution of these characteristics across OMSCS course sections, there are few significant differences. The largest section (414 students) has significantly more women and fewer White students than the average of the other sections, which is a potential limitation for our analysis, due to the possible correlation of class size and race/gender.

3.4. Analytic methods

Our study of graduate student participation in online learning platforms for master's-level courses in computer science involves both descriptive and regression analysis. Descriptive analysis involves frequencies and means of our Piazza participation and demographic variables and is important for contextualization. We then construct a series of logistic and negative binomial regression models that enable us to control for individual-level factors as well as class size in addressing our research questions and hypotheses. In order to model our binary dependent variables (*Nonparticipation* and *Extreme Lurking*) we use logistic regression models, presented here as odds ratios. To predict the intensity active and passive participation (*Number of Posts* and *Number of Views*), we use negative binomial regressions, a generalized form of count regression. We use a count regression model because this type of frequency data is discrete and not normally distributed (Atkins, Baldwin, Zheng, Gallop, & Neighbors, 2013). Finally, we use ordinary least squares (OLS) linear regression to examine lurking behavior. White, male U.S. citizens are the reference group for all regression models.

4. Results

4.1. Descriptive statistics

Our dependent variables are a set of measures examining total participation and the relationship between active and passive

Table 3
Descriptive statistics: Independent variables.

	Study Population: Enrolled Students in 13 Piazza Courses (n = 1914)				
	Mean or %	min	max	n	sd
Course Section Characteristics					
Course enrollment (# of Students)	221	20	414	13	117.80
Demographics					
Female	15%	0	1	280	0.35
Student Age	32.6	19	64	1914	7.55
White	45%	0	1	864	0.50
Asian	40%	0	1	770	0.49
Hispanic	7%	0	1	125	0.25
Black	5%	0	1	93	0.22
Multiracial	3%	0	1	62	0.18
U.S. Citizen	61%	0	1	1175	0.49
U.S. Permanent Resident	8%	0	1	156	0.27
Temporary Visa or Overseas Alien	31%	0	1	585	0.46

participation (Table 4). We find that a small but substantial number of students (7%) did not participate in any way in their course's Piazza message board, neither reading any other students' posts nor posting anything on the course website. Of students who did participate at least once (1777 students), they viewed an average of 292 posts and posted an average of 24 times over the semester. Regarding participation, 90% of students posted at least once, while the remaining 10% only participated passively by reading posts (referred to here as "extreme lurkers" to reflect their engagement in the Piazza community). Finally, our continuous lurking index (of passive to active participation) has a mean of 0.87 and ranges from −0.33 to 1, showing a tendency toward more passive than active course participation.

4.2. Regression models

To address our research question of whether there are any systematic differences in participation in online courses using the Piazza platform, we constructed a series of regression models to examine whether or not students participate, and the nature and intensity of their participation.

To address our first research question "to what extent do graduate students participate in online learning discussion boards?", we constructed a logistic regression model to examine whether any demographic groups were more or less likely to participate, while also controlling for class size (Table 5). Results show that for the most part, gender, race/ethnicity, citizenship, and age do not influence the likelihood that students will or will not participate in the Piazza forum. However, there is one notable demographic exception. Black students are twice as likely (odds ratio = 2.119) as White students to not participate at all on Piazza. Class size also matters, as students in larger classes are more likely to be nonparticipants.

While the likelihood of any participation is important, the intensity and overall patterns of participation show broader student engagement. We hypothesized that women would engage in less active participation in online classrooms. Using the same set of independent variables, we ran a series of negative binomial count regressions to address the intensity of active (posts) and passive (views) participation among students (Table 6). Results do not support our hypothesis. Instead, gender predicts neither active nor passive participation. Women are no more or less likely to post or view items on Piazza.

However, the results show differences by race/ethnicity, partially supporting our second hypothesis that underrepresented minority students would show lower participation. We find that Blacks were less likely to both view (coeff. = −0.315) and post (coeff. = −0.557) than Whites. Asian students showed similar trends (although smaller coefficients) to Black students in terms of fewer posts and views, while results for Hispanic students showed no significant effects. While there are no significant effects on participation arising from citizenship, student age matters for the intensity and type of participation. Older students post on Piazza more than younger students (coeff. = .032), although their viewing behavior does not differ significantly from their younger peers. This partially supports our third hypothesis: we find that older students actively participate more than younger students but find no difference in their passive participation. Finally, in terms of class size, students in large classes appear to post on Piazza less than those in smaller classes, although their viewing behavior remains unchanged.

Our approach acknowledges that participation, and even non-participation, are not binary phenomena. To examine this, we first test whether students are likely to be an "extreme" lurker where they view the message board but never post at all using logistic regression. Results (Table 7) show some demographic differences in which students are more likely to demonstrate this behavior. While Asian and Hispanic students' odds of being an extreme lurker are roughly twice as great as Whites (coeff. = 1.973 & 2.061, respectively), women, Blacks, and international students are not more likely to be or not be an extreme lurker.

We expect that passive participation may vary in the extent to which students "lurk" in the online classroom setting. Given this, we operationalize lurking as a normalized ratio between passive and active participation using a modified E/I index (which ranges from −1 to +1). Results (Table 8) show few differences across the different groups of students. Regarding race/ethnicity, only Asian students are more likely to lurk more than Whites (coeff. = 0.029). There are no gender effects, but age matters, where older students are less likely to lurk than younger students (coeff. = −0.004). Finally, and not surprisingly, class size is also a factor, where students in larger classes tend to lurk more (coeff. = 0.0003).

5. Discussion

Our research adds to a growing, yet still limited body of work that examines online classroom participation patterns (Bliss & Lawrence, 2009; Diep et al., 2016; Goggins & Xing, 2016; Kim, 2013; Malinen, 2015; Song & McNary, 2011), and variation by gender (Barrett & Lally, 1999; Herring, 2000; McSporran & Young, 2001; Rovai & Baker, 2005) and other demographic factors (Diep et al.,

Table 4
Descriptive statistics: Dependent variables.

	Mean or %	min	max	n	sd
Participation Measures					
Piazza Nonparticipant	7%	0	1	1914	0.26
Extreme Lurking	90%	0	1	1777	0.30
Number of Views of Piazza Posts	291.90	1	689	1777	183.43
Number of Posts on Piazza	23.50	0	524	1777	37.55
Lurking Index	0.87	-.33	1	1777	0.15

Table 5
Logistic regression results: Non-participation.

	Non-Participation in Piazza (n = 1912)						
	Odds Ratio	se	std (OR)	z	p(z)	95% LLCI	95% ULCI
Course Section Characteristics							
Class Size	1.004	.001	.501	5.650	.000	1.003	1.006
Demographics							
Female	1.237	.289	.075	.910	.362	.783	1.956
Age	1.003	.012	.026	.280	.780	.980	1.028
Asian	1.146	.281	.067	.550	.580	.708	1.854
Black	2.119	.713	.162	2.230	.026	1.095	4.098
Hispanic	0.870	.366	-.034	-.330	.740	.381	1.984
Multiracial	1.968	.856	.120	1.560	.120	.839	4.617
Temp Visa or Overseas Alien	0.981	.233	-.009	-.080	.937	.616	1.563
U.S. Perm Resident	0.781	.280	-.068	-.690	.490	.387	1.577
Constant	0.021	.001		−8.170	.000	.008	.053
Reference group White, male U.S. citizens							

Table 6
Negative binomial count regressions: Participation intensity.

	Passive Participation Intensity (Number of Views, n = 1775)						Active Participation Intensity (Number of Posts, n = 1775)					
	B	se	z	p(z)	95% LLCI	95% ULCI	B	se	z	p(z)	95% LLCI	95% ULCI
Course Characteristics												
Class Size	.000	.000	-.710	.480	-.001	.000	-.003	.000	−10.670	.000	-.004	-.002
Gender and Age												
Female	.062	.057	.610	.544	-.102	.192	-.077	.087	−1.050	.295	-.277	.084
Age	.002	.003	.520	.600	-.005	.009	.032	.004	7.220	.000	.022	.039
Asian	-.108	.052	−1.680	.093	-.253	.019	-.219	.078	−2.740	.006	-.391	-.065
Black	-.315	.096	−3.220	.001	-.640	-.156	-.557	.148	−4.260	.000	-.950	-.352
Hispanic	-.072	.081	-.590	.552	-.277	.148	-.214	.124	−1.530	.125	-.466	.057
Multiracial	-.148	.113	−1.380	.167	-.494	.085	-.126	.173	−1.050	.293	-.548	.165
Temp Visa or Overseas Alien	.004	.052	.050	.961	-.131	.138	.004	.077	-.010	.989	-.162	.160
U.S. Perm Resident	.024	.077	.440	.657	-.157	.248	-.154	.117	−1.100	.270	-.382	.107
Constant	5.605	.010	42.250	.000	5.378	5.901	2.751	.153	16.970	.000	2.467	3.111
Reference group White, male U.S. citizens												

Table 7
Logistic regression: Extreme lurking behavior.

	Extreme Lurking (n = 1775)						
	Odds Ratio	se	std (OR)	z	p(z)	95% LLCI	95% ULCI
Course Section Characteristics							
Class Size	1.000	.001	-.041	-.510	.607	.998	1.001
Demographics							
Female	1.100	.241	.027	.350	.723	.706	1.653
Age	0.991	.012	-.074	-.840	.401	.968	1.013
Asian	1.973	.435	.325	3.030	.002	1.263	2.981
Black	1.876	.726	.118	1.420	.154	.814	3.672
Hispanic	2.061	.649	.182	2.340	.019	1.127	3.853
Multiracial	1.404	.691	.049	.560	.573	.505	3.443
Temp Visa or Overseas Alien	1.380	.276	.149	1.630	.104	.936	2.042
U.S. Perm Resident	0.762	.261	-.065	-.700	.484	.404	1.536
Constant	0.086	.038		−5.530	.000	.038	.211
Reference group White, male U.S. citizens **(n = 1775)**							

2016; Du et al., 2015; Ke, Kwak, 2013; Rovai; Ponton, 2005). With increasing implementation and related study of online graduate curricular programs, these lines of inquiry and others asked in the growing corpus of research may lead to the development of a stronger empirical base for understanding online graduate student experience and behavior. We sought to answer three overarching questions: (1) to what extent do students participate in courses (as operationalized by online learning discussion boards), (2) for those who participate at all, what are the patterns of their engagement; and (3) how does online participation vary by students' demographic characteristics?

Table 8
OLS regression: Lurking index.

	Lurking Index (n = 1775)						
	B	se	β	t	p(t)	95% LLCI	95% ULCI
Course Characteristics							
Class Size	0.0003	.000	.212	9.220	.000	.000	.000
Demographics							
Female	.008	.010	.019	.840	.404	-.011	.028
Age	-.004	.000	-.200	−8.730	.000	-.005	-.003
Asian	.029	.009	.094	3.170	.002	.011	.046
Black	.029	.017	.041	1.740	.082	-.004	.062
Hispanic	.024	.014	.039	1.680	.093	-.004	.051
Multiracial	-.001	.020	-.001	-.040	.968	-.039	.038
Temp Visa or Overseas Alien	-.006	.009	-.020	-.710	.477	-.024	.011
U.S. Perm Resident	.011	.013	.021	.830	.408	-.015	.037
Constant	0.927	.017		54.300	.000	.893	.960
R-squared	0.105						
Reference group White, male US citizens							

5.1. Participation patterns in online graduate courses

First and foremost, our results show that student engagement in online discussion groups does not fall into distinct categories. Instead, it is a continuous phenomenon that is situated along a continuum ranging from active to passive participation. In line with the existing body of research (Dennen, 2008; Hrastinski, 2008; Kim, 2013; Nonnecke; Preece, 2000; Xie et al., 2014), we differentiate between active and passive forms of participation, but do so in less absolute terms.

Our findings indicate that participation in online degree program classrooms may be quite different from the low participation patterns that prevail on social networking sites (Van Mierlo, 2014) or in massive open online courses (Rieber, 2017). We find that over 90% of the students actively participated by posting at least once, with an average of over 20 posts and nearly 300 views (Table 4). This finding contrasts the widely-held conception that 90% of members of online communities do not participate at all, 9% contribute occasionally, and 1% create the majority of content (Arthur, 2006; Van Mierlo, 2014). From the perspective of quantitative participation patterns, the fully-online degree program environment may be even more similar to in-person classrooms than originally thought. However, it is difficult to disentangle the program's causal mechanism between technological effects, the older population, the graduate degree setting, and the computer science discipline (and correspondingly high computing literacy). Further, while the Piazza platform is the required communication and participation mechanism, it excludes other forms of online engagement that students may develop organically and outside of the university platform. Thus, while our discoveries related to participation rates are distinct from other studies, they do not encompass other ways that students may use to engage and exchange course-related information. Application of theories of informal learning, for example (Conrad, 2008), might help to explain motivation and interest in participating within this required platform, while also engaging in other non-school platforms. Other studies have used social network theory (Lin, 2008) to examine how networks of online participation form learning communities and enhance learning outcomes (Diep et al., 2016; Hernández-García, González-González, Jiménez-Zarco, & Chaparro-Peláez, 2015).

Our results also show that online class size matters for understanding participation patterns in the virtual classroom. As the Lurking Index shows, large classes experience a relatively greater drop in active participation than passive participation, meaning that students posts less on average, but view roughly the same amount of content (Table 8). Therefore, our findings suggest that class size should not be dismissed easily in the design and implementation of online education. They also suggest linear measures of class size are most appropriate in studies of online classrooms, instead of tiered or cutoff measures. In the light of debates about the scalability of online courses and the increasing affordability of education, our data suggest that there is a potential tradeoff to be made between class size and student participation.

The nature of the Piazza data and required classroom use enables us to measure lurking behavior in ways that have not been addressable across multiple graduate classes. Our results not only show variation in participation rates, but also help to delve more deeply into lurking behavior. Methodologically, our adaption of the E/I index, typically used in social network research, to the online participation context via the Lurking Index shows promise as a measure of participatory behavior that can uncover variation in participation, complementing analyses that examine changes of simple intensity. It reveals that relative rates of active and passive participation vary across demographic groups and demonstrates how participation patterns change in large classes. For example, our Lurking Index shows that differences in participation between Asians and Whites are not simply in overall intensity, but also in the manner of their participation, something not visible in count regressions (Table 8). The ability to see relative differences in active and passive participation and to compare them is useful in understanding the interplay of forms of online participation, allowing us to address new questions about the nature of participation. Our findings also contribute to the ongoing development of a theory of online learner participation (Hrastinski, 2008, 2009), which currently does not incorporate demographic variations in online participation.

5.2. Demographic effects in online participation

Our research has also been enabled by access to detailed demographic data alongside online participation data. The nature of identifiable online participation data meant that we could examine participation across gender and race/ethnicity as well as age, something not always possible in studies of online behavior. Our results align with prior research that did not identify any significant gender differences in online participation rates (Balaji & Chakrabarti, 2010; Davidson-Shivers, Morris, & Sriwongkol, 2003; Guiller & Durndell, 2007; Masters & Oberprieler, 2004), although none of these studies were conducted in a STEM research setting. Some studies have theorized that equal gender participation rates may be attributable to missing social cues in online discussion boards (Balaji & Chakrabarti, 2010; Dubrovsky, Kiesler, & Sethna, 1991), which may help to reduce gender stereotypical judgements (Cheryan et al., 2009), contribute to an increased sense of belonging of women to online communities (Cheryan et al., 2009), and have a democratizing effect on communication (Balaji & Chakrabarti, 2010; Guiller & Durndell, 2007). However, we advise caution in taking our finding as evidence that online education has such an equalizing effect on the gender participation gap in STEM. Instead, it is possible that our finding reflects the advanced nature of this graduate degree program and the low population of women (15%). This could also explain why our finding contradicts other studies that find higher active and passive participation rates of women in an online computer science course, although at the undergraduate level (McSporran & Young, 2001; Yukselturk & Top, 2013). This study is one of the first that examines demographic differences in participation rates in an online graduate degree program and provides an avenue for future research to examine to what extent female undergraduate and graduate students differ in an online STEM classroom.

Informed by theories of social identity (Tajfel, 1978) and sense of community (McMillan & Chavis, 1986) as well as empirical evidence showing that underrepresented minorities report a lower sense of belonging in virtual classrooms, possibly due to racial bias and stereotyping (Rovai & Ponton, 2005), we expected underrepresented minorities to exhibit lower rates of active participation than Whites. However, our hypothesis held true for Black students and not Hispanic students, demonstrating that grouping underrepresented populations together as a single group can mask important differences (Table 6). We also find that Black students are more likely than any other group to be nonparticipants (not accessing the discussion group even once) (Table 5), thereby failing to achieve what Hrastinski (2008) identified as the very first level of online participation. However, it is possible that this effect is at least partially a spurious effect of class size, rather than a demographic effect. Our sensitivity analysis showed that the Black-White nonparticipation difference becomes non-significant once we exclude the largest class section in our dataset (in which Black students are overrepresented).

Finally, our Lurking Index shows that, once we control for class size, underrepresented minorities are no more likely to lurk than Whites, whereas the effect persists for Asian students (Table 8). This finding is particularly interesting against the background of a recent study showing that the negative effect of increased class size on classroom participation is more pronounced among underrepresented minorities (Beattie & Thiele, 2016). Unfortunately, our sample of Black students is too small to allow us to conduct a subgroup analysis on how participation varies for Hispanics and Blacks with increasing class size.

Results also show that Asian students in the OMSCS program participate much less than Whites in the online graduate classroom overall. Whether this finding is attributable to cultural differences or language factors remains an open question (Table 6). Some studies suggest that Asian students may be more accustomed to the structured, lecture-centered learning style of a traditional classroom and may struggle to adapt to the discussion-based learning style of online classrooms, resulting in lower active participation rates (Biesenbach-Lucas, 2003; Liu et al., 2010). Others have theorized that students with limited English proficiency may feel discouraged to participate in online discussion boards due to difficulties in understanding course content and effectively communicating opinions in another language (Gunawardena et al., 2001; Liu et al., 2010), but this hypothesis is contested (Biesenbach-Lucas, 2003). While we do control for student's citizenship status and, therefore, to some extent for possible cultural differences between Asian-American and Asian international students, our data does not allow us to account for students' English-speaking proficiency. This is potentially an area for further inquiry, particularly given that prior studies have seldom examined Asian students' participation in online classrooms.

Finally, we find that older adults engage in more active participation (Table 6) and lurk less (Table 8) than younger students. This finding reflects that older adults in advanced education settings seem to be different than younger learners in their self-direction and competence. As such, our finding extends to the theory of adult learning (Knowles, 1989), which posits that adults have a profound need to be self-directing in their learning, exhibit a strong goal-orientation, are deeply engaged in their learning process, and take responsibility for their own learning advancement. Although this study does not examine content quality, these findings suggest that online program designers may "seed" older learners across class sections to help generate discussion.

6. Limitations and future research

Admittedly, this study is exploratory and advantaged by access to detailed student demographic data. Despite our large sample size spanning multiple computer science courses, our data come from a single online degree program in one STEM discipline at one US institution. Additional research incorporating multiple disciplines and preferably at multiple institutions would enhance the generalizability of our work. Therefore, we advise caution in generalizing our findings to other STEM or non-STEM online degree programs. Further, we only examine the quantity of online participation, not its quality. We acknowledge the criticism that has been raised in other studies about the limitations of assessing only participation frequency without analyzing the message content and depth of interactions (Kim, 2013; Masters & Oberprieler, 2004). Again, mixed-methods studies are needed to adequately assess participation and, ultimately, *learning* in online degree programs. Further, students are likely to also use communication platforms and tools not provided by the institution to interact and collaborate with fellow students. It is possible that some students prefer those external platforms and participate less frequently on Piazza. However, course instructors and teaching assistants only use Piazza to communicate with students, limiting the utility of alternate platforms. Also, course syllabi explicitly encourage online participation by stating that students have to check Piazza regularly and pose course-related questions publicly instead of sending private messages to the instructor or course staff. As such, Piazza constitutes the virtual classroom and provides the central hub for students to communicate with their peers, professors, and teaching assistants.

Finally, there are limitations and opportunities presented by this research. Most notably, we know nothing of individual student experience or motivation to engage on Piazza, as well as their perceived value for this interaction. Our prior work (Kreth, Spirou, Budenstein, & Melkers, 2019) showed that almost half of OMSCS students have previous experience with online courses. We, and others, should take student perspectives and online educational experiences into account in future studies of participation. Related, our study is cross-sectional and is, therefore, limited in its ability to capture student learning and development. Future work should also be longitudinal, which would enable researchers to examine, for example, the effects of prior experiences on later participative behavior, changes in perceptions over time, and other related issues. Our preliminary work here suggests that this approach could be valuable and add additional insight to online participation of adults in the graduate learning environment.

7. Conclusion

With most literature on the topic of online participation being generated in single-class or MOOC settings, there remain numerous questions about the student experience pursuing fully-online degrees, at both the baccalaureate and graduate levels. These questions are particularly pressing, given the rapid growth of online degrees, including fully-online programs offered by traditional universities (Hanover Research, 2014; Seaman, Allen, & Seaman, 2018). However, measures of participation must continue to improve in order to understand the nuanced patterns of student behavior in online classrooms, especially among students who are socialized to the online learning environment. More research is needed to inform best practices and evaluation of these emerging online degree programs, particularly given the unique participation patterns noted in this study, which are very different from those in online social communities.

Further, our study makes substantive empirical contributions to the limited body of research on demographic variation in online participation. Existing studies have rarely, if at all, examined more than one demographic group at a time. This is an important limitation given the age and racially/ethnically diverse online student population consisting of US domestic and international students and students who are at different stages in their career (Dabbagh, 2007; Ke, Kwak, 2013). This diversity possibly results in heterogenous individual characteristics that may impact online participatory behavior differently. In our study, we incorporate a wide range of student characteristics and show that the intensity of students' active and passive participation varies on different demographic traits.

CRediT authorship contribution statement

Isabel Ruthotto: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing. **Quintin Kreth:** Conceptualization, Data curation, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing. **Jillian Stevens:** Data curation, Conceptualization. **Clare Trively:** Conceptualization, Data curation. **Julia Melkers:** Conceptualization, Methodology, Supervision, Writing - review & editing.

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Appendix A. Supplementary data

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