Debugging the Divide

Exploring Men's and Women's Motivations and Engagement in Computer Science MOOCs

by

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Preface

I have always had a love for learning. As a child, I often read science books about anything from volcanoes to electricity. While I do not do that as much as I did back then, I am still a strong believer in lifelong learning. During my minor in education, I had the opportunity to be in front of the classroom, being the teacher instead of being taught. I loved the interactions I had with my students and the impact that I could have on them. While teaching computer science is meaningful work to me, I did notice a significant gender gap in my classes. Combined with noticing this in my studies and in my work as a programmer, this has never left the back of my mind. When I was taking a course given by Marcus Specht, my thesis advisor, I came into contact with Shirley de Wit, my daily co-supervisor. We discussed multiple ideas related to gender and computer science, which brought forth this master thesis.

I would like to start off by thanking my thesis committee for their supervision, feedback, and advice. To Shirley, I want to thank you extensively for your critical feedback, and also for all the ideas that you gave me. I learned a lot from your views on research and how to communicate my ideas. I also thoroughly enjoyed our conversations outside my research. To Fenia, my daily supervisor, I want to thank you for providing useful feedback and always having a positive mindset about my thesis, even when I was running into problems and not making the progress I wanted. This was hugely motivational, so thank you. I also want to thank the entire research group of LDE-CEL. I could not have wished for a more welcoming research group. This research could not exist without MOOC data, which was delivered by the TU Delft Extension School, so I would like to extend my thanks to them as well. Additionally, I would like to thank all my family and friends who have supported me throughout the entire process, and in particular my parents. Finally, I would like to thank Clare for her unwavering support throughout this journey. Your encouragement has been invaluable.

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Summary

Within the field of computer science (CS), women are under-represented in the workforce and education settings. As Massive Open Online Courses (MOOCs) grow in popularity, understanding the gender differences in reasons for enrolment and engagement remains crucial to improving learner outcomes. This study investigates why men and women enrol in introductory CS MOOCs and how they interact with these courses. This is done with data from four MOOCs offered by TU Delft between 2015 and 2022.

Using survey data for the learners' reasons for enrolment and clickstream data for their behavioural engagement, we applied k-means clustering to identify engagement patterns. Our analysis reveals that the three most important reasons for men and women are career-related, interest-related, and degree-related, in that order. Women are more likely to enrol for career-related reasons than men, while men are more driven by interest in the topic than women. Women also tend to show lower engagement levels compared to men, who are more likely to complete the courses. We found no significant association between reasons for enrolment and engagement for men and women.

These findings highlight the need for gender-sensitive course design strategies to enhance engagement and completion rates. Providing mentorship opportunities, fostering peer interaction platforms, and highlighting role models in the field could also help create a more inclusive learning environment. Future research should explore specific learner challenges and incorporate a more comprehensive engagement model.

Contents

1 Introduction

Women are under-represented in many disciplines within Science, Technology, Engineering, and Maths (STEM). This trend is also visible in computer science (CS), where women hold fewer undergraduate degrees than men [17]. This significantly impacts the global economy, leaving a workforce shortage in CS jobs worldwide [73, 78]. Furthermore, the lack of women in STEM causes a decrease in entrepreneurial activity [34] and innovation [10]. This gender gap is attributed to many reasons, such as stereotypes within teaching materials, pressure from society to fill gender roles, and the environment around girls steering them away from CS [21, 53]. Recent educational initiatives in high schools and beyond are attempting to make CS education more inclusive [3, 55, 85].

One of these initiatives promoting inclusivity in CS is Massive Open Online Courses (MOOCs). MOOCs are online courses which are usually offered for free, with no limit on the number of enrolments. Agarwal, the CEO of EdX[1], said that "MOOCs make education borderless, gender-blind, race-blind, class-blind and bank account-blind" [1]. MOOCs make it possible to obtain higher education for a larger population [98]. This also includes groups which were previously underserved by education, such as women who assume multiple roles in life [28]. MOOCs allow women to learn CS with fewer obstacles due to MOOCs' anonymous nature. However, the gender gap within the field of CS is also visible in CS MOOCs [36]. Women are therefore missing out on the enhanced skill development, career advancements, and salary increases that people who complete MOOCs get [50].

1.1. Problem statement and aim of research

MOOCs often suffer from high dropout rates [81]. Most MOOCs have a completion rate of 13% or lower [81]. Likewise, this is also the case for CS MOOCs [90]. Women have previously been observed to have a lower persistence than men in CS MOOCs [26, 36], meaning women stop engaging earlier with MOOCs and fewer women complete them. While this effect has been observed for CS MOOCs, there is a lack of research which answers whether women also have lower persistence in introductory CS MOOCs.

According to Crues et al. [26], what parts of the MOOC the learner interacts with can be influenced by the learner's reason for enrolling. A learner who is interested in the topic of the MOOC, for example, may be content with watching some of the videos, while a learner who wants to advance in their career may interact with more of the MOOC to learn the most they can from the MOOC. While they found a significant association between gender and reasons for enrolment, the differences were small. This research was also done on only one single MOOC. Luik et al. [71] found that enrolment in programming MOOCs is largely due to intrinsic motivation instead of extrinsic motivation. The association between gender and reasons for enrolment in introductory CS MOOCs is largely unresearched.

Finally, little research is available about the association between these reasons for enrolment and engagement in introductory CS MOOCs. Crues et al. [26] finds no association between reasons for

[1]An online platform that offers MOOCs.

enrolment and persistence, but again, this research is done on a single MOOC.

In this research, we aim to fill the identified research gap about reasons for enrolment in introductory CS MOOCs by doing a study on multiple introductory CS MOOCs to gain a better understanding as to why men and women enrol in introductory CS MOOCs. Significant differences can indicate to course designers that male and female learners also have different expectations from the MOOCs, which would aid in the design of new MOOCs, as well as help iterate on current MOOCs. Similarly, we aim to explore the behavioural engagement of men and women in introductory CS MOOCs. If we understand the differences in behavioural engagement between men and women and the moment in the MOOC at which learners disengage, interventions can be designed around this. Finally, we want to discover if there is any association between reasons for enrolment in introductory CS MOOCs. Depending on whether there is a significant association between the two, course material may be targeted towards reasons for enrolment to increase MOOC engagement.

1.2. Research questions

Based on the problem and the objective of this investigation as defined in section 1.1, the following research questions are posed:

RQ1: What are the differences in reasons for enrolment between men and women in introductory computer science MOOCs?
RQ2: What are the differences in behavioural engagement between men and women in introductory computer science MOOCs?
RQ3: How do reasons for enrolment influence behavioural engagement among men and women in introductory computer science MOOCs?

In the context of this research, behavioural engagement refers to the degree to which students participate in MOOC activities.

To answer these research questions, this study employs a mixed methods approach. We integrate qualitative and quantitative methods to provide a detailed examination of gender differences in motivations and engagement.

For research question 1, closed-ended and open-ended responses to a pre-course survey are analysed to understand the motivations behind enrolling in the MOOC. A descriptive, quantitative method is used for the closed-ended responses to determine if there are statistically significant differences in the enrolment reasons provided by men and women. The open-ended responses will be analysed qualitatively. Combining these methods will give us a more complete understanding of reasons for enrolment in introductory CS MOOCs.

Research question 2, which explores learners' behavioural engagement with MOOCs, employs a modified approach based on the work by Kizilcec et al. [65]. Participants are clustered into four groups using k-means clustering, an unsupervised machine learning technique. This clustering is based only on learner interactions with the MOOCs, ensuring an unbiased grouping based on engagement behaviours. We employ a descriptive, quantitative method to assess differences in engagement patterns between men and women, providing quantitative insights into how different genders engage with the course material.

Finally, research question 3 examines how enrolment reasons influence engagement differently for men and women. Participants are divided by gender and by their reasons for enrolment in the MOOC. Then, they are categorised into the previously identified engagement clusters. The association between enrolment reasons and engagement for both genders is analysed using statistical methods to identify any significant patterns. This part of the analysis integrates the reasons for enrolment with the quantitative engagement metrics, which brings an understanding of the influence of reasons for enrolment on engagement. For this research question, only the closed-ended responses will be used, as they do not require the interpretation needed for open-ended responses.

2 Background: Women in Computer Science

In this chapter, we discuss the existing body of literature on the statistics on gender disparities in computer science (CS), why these disparities exist, and what the impact of these disparities is. The overarching goal is to provide a comprehensive understanding of the factors influencing gender disparities in CS education and place this research in a broader context within the observed gender gap in CS.

2.1. Definition of Terms

To ensure clarity throughout this research, definitions for some key terms used in the related literature will be provided. Specific statistics or research for fields like computer science, Information and Communication Technology (ICT), or Information Technology (IT) are often unavailable. Therefore, we will always make these distinctions when discussing previous research.

Science, Technology, Engineering, and Mathematics (STEM) is a term first introduced by Judith Rahmaley in 2001 [67]. It includes all technical disciplines, including CS.

Computer Science (CS) is defined by Denning [33] as “the body of knowledge and practices used by computing professionals in their work”. This discipline is fundamental for software development, computer systems, and data analysis. It is central to fields such as artificial intelligence, database management and security.

Information Technology (IT) refers to the use of computers, networking, and other physical devices, infrastructure, and processes to handle all forms of electronic data.

Information and Communication Technology (ICT) is an extension of IT that includes communication technologies such as the internet, wireless networks, cell phones, and other communication mediums. ICT includes broadcast media technology, telecommunications technology, and different kinds of communication networks. In Dutch, the term ‘IT’ has largely fallen out of favour compared to the term ‘ICT’.

Figure 2.1 shows the relationship between these four terms.

2.2. Gender disparities in Computer Science

While the field of CS has grown drastically over the past decades, a large gender gap has been observed in educational, research, and professional environments. In this section, we will highlight the historical trends, as well as the current state of the gender disparity in CS.

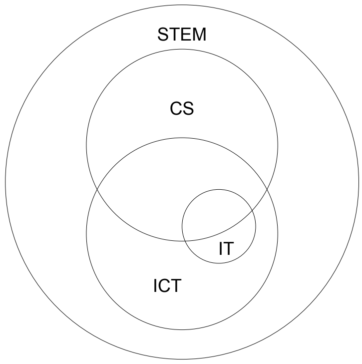


Figure 2.1: The relationship between STEM, CS, IT and ICT

2.2.1. A brief history of women in Computer Science

Women contributed significantly to the field of CS. Some examples are: Ada Lovelace, who wrote the first computer program; Grace Hopper, who made significant contributions to the field, among which is the first compiler; and Margaret Hamilton, who helped NASA put the first people on the moon [45]. These women, among many others, helped move CS forward to the field we have now. Before computers were invented, *computer* was a job title. This was someone who did calculations, someone who *computes*. Surprisingly, this used to be a female-dominated job. At the time, this was viewed as low-skilled work, similar to clerical work. Around the 1960s, this started to change. To increase the status of programming, men working in the field threw up barriers in education and the work field which generally favoured men, such as personality tests. The historian Nathan Ensmenger argues that this is the basis for the modern stereotypes about programmers that many of us have right now [43].

2.2.2. Recent statistics

This leads us to the current situation, where CS is now a predominantly male field. In CS research, it is estimated that only 15 to 30% of the authors of published papers are women [40]. According to a report from 2020 from the National Center for Education Statistics, the percentage of postsecondary degrees awarded to women within ICT fluctuates between 11.5% and 35.9%, averaging out to 21.7% across all countries [80]. This average is the lowest across all fields for which data was collected. In the Netherlands, the percentage of ICT degrees awarded to women was 16.2% [80]. We see similar statistics in the workforce. In a report from the International Labour Organization Department of Statistics from 2018, female participation in the ICT workforce ranges from 3% to 59%, averaging out to 30.8% [57]. In the Netherlands in 2018, 17.3% of the ICT workforce is female [57].

2.3. Barriers to entry for women in Computer Science

Across STEM fields, it has been noted that women have higher dropout rates in various stages in their journey towards a career in STEM, the so-called 'leaky pipeline', "(...) carrying students from secondary school through university and on to a job in STEM" [21]. There is not just one party or factor that carries all the blame. The existence of this pipeline results from a combination of societal, cultural, educational and psychological barriers.

2.3.1. Societal and cultural barriers

Stereotypes and bias

Some studies discuss the effects of stereotype threat [9, 96], which is described as the "uncomfortable feeling that arises when people are at risk of confirming a negative stereotype in the eyes of others" [97]. In the case of CS, that means that women think they may be worse computer scientists. A survey of directors of women in engineering programs showed that they believed women's low self-confidence was the most important obstacle for women in STEM [39]. Stereotypes regarding CS can be both positive and negative. For some women, positive stereotypes contribute to a sense of belonging in the field [18].

Figure 2.2 describes the types of stereotypes people hold about the culture of CS, as well as the ability

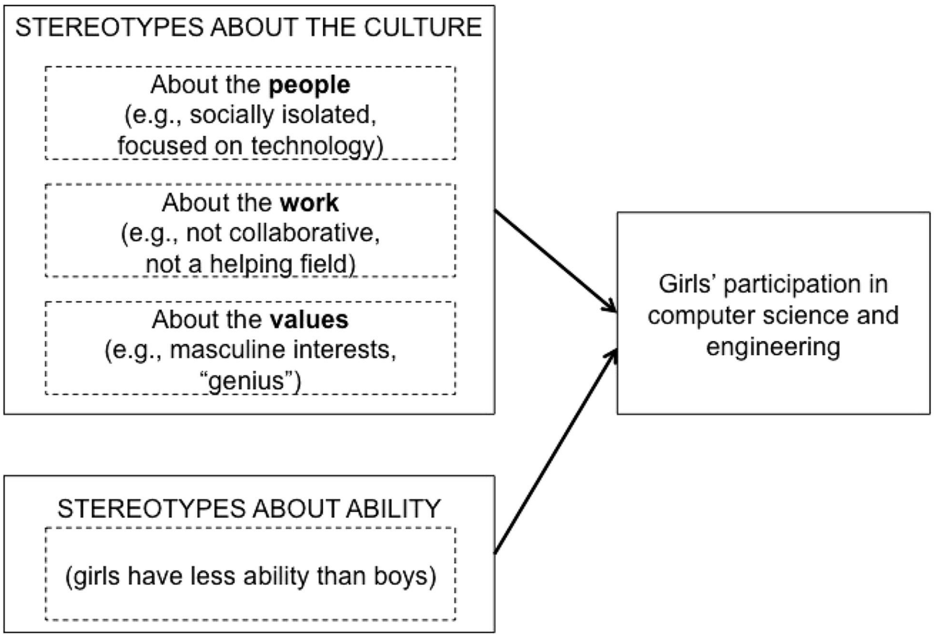


Figure 2.2: Common stereotypes held regarding CS from Cheryan et al. [17]

of girls to thrive in CS. Some studies have suggested that fields such as CS do not align with social values, which women often hold [37]. CS is seen by many as an antisocial field which lacks social interaction [102, 19]. Some STEM fields share this stigma, while others do not. While women hold about 50% of the undergraduate degrees in fields like law, biology, chemistry, and maths, they hold less than 20% of the CS and engineering degrees [17]. Life sciences, such as biology or chemistry, are seen as more "social" than physical sciences, such as engineering or CS [82], which may contribute to the lower percentage of women studying CS. This lower percentage of women in the field is also mentioned as a reason why girls do not pursue a CS education, maintaining the gender gap [56]. An effective way to reduce the impact of negative stereotypes to get more girls in STEM is by exposing them to female role models in the field [46].

Role models

Role models, whether they be male or female, can play an important role in recruiting girls into STEM fields [35]. Female role models specifically can contribute to higher female retention within STEM fields [75]. Within CS, role models who exhibit stereotypical traits and behaviours have been observed to negatively affect women's interest in studying the field due to a reduced sense of belonging [16]. Similarly to Drury et al. [35], Cheryan et al. [16] found that the gender of the role model has no significant effect in creating interest in studying CS.

Media and pop culture representation

Just as role models can influence women's interest in CS, media and pop culture representation also play a crucial role. In Cheryan et al. [19], a group of undergraduate students was exposed to either a stereotypical or non-stereotypical news article about CS. The women's desire to major in CS rose significantly when exposed to non-stereotypical news, while the men's desire stayed on a similar level. The lack of representation of women in STEM in popular media may also contribute to a lowered interest in CS among women [93].

Barriers in the workforce

Women in the ICT workforce encounter many different challenges that are not only influenced by traditional gender roles, but also include institutional barriers, workplace discrimination, and lack of equitable opportunities for advancement [88]. Fragmented career paths are more common for women in the ICT sector, partly due to the fact that women often assume more family responsibilities under the 'male breadwinner' model [101]. This model not only limits their time but also their availability to engage in the substantial self-learning required by ICT jobs, which frequently requires workers to continue education outside of standard work hours.

2.3.2. Educational and psychological barriers

Self-efficacy

A common explanation for the high attrition rate for women is the observation that women show lower self-efficacy in CS compared to men [12, 24]. *Self-efficacy theory* is the theory that self-efficacy, an individual's belief in their ability to perform actions to achieve certain goals, influences the effort and persistence they invest in overcoming challenges [6].

According to Bandura [7], self-efficacy is affected by four sources of information.

- Performance accomplishments: Successfully accomplishing a task, can increase a person's self-efficacy beliefs. On the other hand, repeatedly failing at a task can lower a person's self-efficacy beliefs. Bandura considers this to be the most influential source of information affecting self-efficacy.
- Vicarious experiences: Experiences or feelings caused by someone else can also influence self-efficacy. For example, seeing a role model perform a task successfully can help a person's belief that they, too, can perform that same task. While self-efficacy is not improved at a similar level as with performance and accomplishments, role models can still have a positive influence on a person's self-efficacy beliefs. It has also been noted that diverse role models performing the same task successfully has a more positive influence compared to one single role model.
- Verbal persuasion: Another source of information that can affect self-efficacy beliefs is verbal persuasion. Through verbal persuasion, people's self-efficacy beliefs regarding a task can improve. However, similarly to vicarious experiences, one's own accomplishments remain a stronger influence.
- Emotional arousal: This is a person's physiological state, which has an impact on the way they perceive their levels of anxiety and stress in relation to a task. When a person is in a calmer state, they judge their anxiety and stress levels regarding that task to be lower, causing them to judge their chances of successfully completing that task to be better.

Women have been observed to have a lower computer self-efficacy compared to men, even when controlling for experience, knowledge, and computer anxiety [51]. Women (incorrectly) believe that they have less natural ability in fields dominated by men, such as CS [11].

Chilly classroom climate

Classroom climate describes the social aspect of the learning space, including not just the physical surroundings, but also the emotional and social factors that either help or hinder learning in these settings [44]. The classroom climate is impacted both by student-student interactions, as well as student-teacher interactions [92]. Teachers engage with their classes through giving lectures, tutoring, answering questions and more [8]. Students engage with each other by talking and working together to solve a problem [8]. Warrington & Younger [105] found that many science teachers still had lower expectations of girls when compared to boys, contributing to a disinterest in science from the girls [21]. A non-inclusive classroom environment in STEM can cause women to drop out [47]. A classroom climate can be made more inclusive by highlighting important contributions of marginalized groups, making equitable course decisions and including students' interests in course design [64]. MOOCs may be an effective way to bypass the traditional classroom environment by creating a more individual learning experience and therefore possibly avoiding the leaky pipeline often faced in STEM education [54].

In conclusion, there are many factors that contribute to the gender gap in STEM and in CS in particular. The barriers to entry discussed here, such as cultural stereotypes, lack of role models, and the educational environment, represent only a selection of the challenges faced by women.

2.4. Impact of gender disparity in Computer Science

The gender disparity in CS poses challenges for equity and significantly influences the field's development and output. This section examines the economic and innovative impacts of this disparity. It highlights the critical need for more inclusive workforce strategies in response to growing ICT worker shortages.

2.4.1. Economic implications

The technology sector is one of the fastest-growing industries, consistently generating a high demand for skilled workers [14]. Meanwhile, the shortages of ICT workers are increasing in the Netherlands [100]. This need for talent in the technology industry highlights the importance of addressing gender disparities to ensure that this employment gap can be filled. In addition, jobs in the technology field often offer higher salaries compared to many other sectors. Given that women only hold $\approx$30% of positions in ICT [57], they do not benefit as much from the high salaries in this field, which contributes to the overall gender wage gap.

2.4.2. Implications on team diversity and innovation

Diversity within teams is not just a matter of equity but also innovation. Diverse teams are more likely to produce creative solutions and view problems from multiple perspectives [72, 52]. Companies with greater gender diversity also tend to have higher sales and profits [52]. The under-representation of women in CS means that teams often miss out on the unique insights and experiences women bring, potentially leading to biases in applications that fail to consider the needs of a wider user base. There are countless examples of women not being part of the design process of a product leading to undesirable outcomes. One example is that women are likelier to get injured in car crashes [13]. The first female crash dummy, named SET50F and designed to take female anatomy into account, was developed only in 2023. Another example is that of voice recognition. Voice recognition software performs worse on female voices compared to male voices, leading women to not buy certain products [5]. A more diverse team in the design and testing stages could, at least in part, mitigate the biases these systems have.

3 Background: MOOCs

Massive Online Open Courses (MOOCs) are online courses first introduced in 2008 [76]. There is no limit on the number of enrolled students, which is why they are “massive”. The “open” indicates that anyone interested can enrol, often free of charge. MOOCs democratise access to education, making it accessible to anyone with an internet connection. This means a broad population has access to higher-level CS education, transcending social, economic and geographical barriers [98].

As shown in the previous chapter, women face significant barriers entering into CS. They continue to face discrimination in the classroom (subsection 2.3.2). MOOCs are seemingly a good fit for lowering the barriers to entry by providing a free, anonymous and flexible way to start learning CS that a traditional education would not be able to provide. In this chapter, we discuss what a MOOC is, the reasons learners enrol in MOOCs, engagement in MOOCs, and the behavioural differences between men and women in MOOCs.

3.1. Anatomy of MOOCs

Understanding the anatomy of MOOCs is important for contextualising the rest of the research. MOOCs can be broadly categorised into two formats: instructor-paced and self-paced. Instructor-paced MOOCs follow a fixed schedule, with course materials and assignments released on a set schedule, often mirroring traditional classroom settings. This format encourages learners to progress through the course simultaneously, creating a sense of community and peer interaction.

In contrast, self-paced MOOCs offer flexibility, allowing learners to access and complete course materials at their own pace. This format is particularly advantageous for individuals balancing education with other commitments, as it accommodates varied schedules and learning speeds.

A typical MOOC consists of video lectures, readings, quizzes, and discussion forums. Video lectures serve as the primary mode of instruction, enabling students to learn from experts regardless of geographical location. Supplementary readings provide in-depth knowledge and context, while quizzes and assignments assess understanding and reinforce learning. Discussion forums facilitate interactions between students and instructors, creating a collaborative learning environment.

For this research, we will be using data from MOOCs hosted on the EdX platform. Therefore, it is important to understand the structure of a MOOC on EdX. Within an EdX MOOC, there is a set structure, as shown in Figure 3.1. In a MOOC, there are multiple chapters. Usually, in an instructor-paced MOOC, one chapter is due in each assessment period. Within a chapter, there are one or multiple sequential blocks. These can be seen as lessons within one chapter. Within one sequential block, there are vertical blocks, which are the components of a lesson. Finally, in the bottom layer, below vertical blocks, is the actual core content of the MOOC. These are problems, quizzes, videos, discussions, and open response assessments (ORAs). Engagement will be measured based on the problem, quiz, video and ORA blocks, since we do not have access to discussion data.

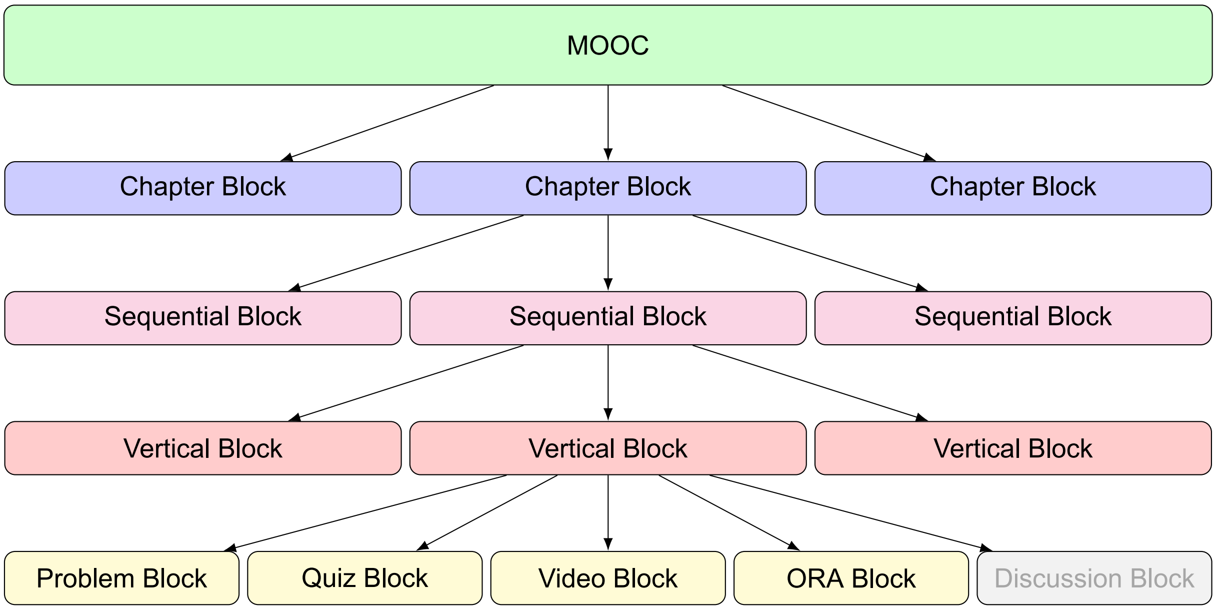


Figure 3.1: Course structure of an EdX MOOC. Discussions are excluded from this research.

3.2. Reasons for enrolment

Motivation is a complex idea that consists of different components: interest, goals, and values, among others [84]. The motivations behind enrolment in MOOCs are as diverse as the learners themselves. Understanding these reasons is important for educators, course designers, and researchers looking to enhance the MOOC experience, improve engagement, and increase completion rates. By mapping out the possible reasons for enrolment, we can better understand the learners and their needs. Crues et al. [26] determine five clusters of reasons participants gave for enrolling in a CS MOOC, which are “Computer Science Student”, “Understanding and Learning”, “Programming is Cool”, “Career and Entrepreneurial Activities” and “Other” for any reason that did not fall into any other category. They found that participants are taking the MOOC for their studies, purely out of interest, a general fascination for programming, for their career, for a more specific reason which does not fall into the other clusters. Although there were significant differences between the reasons for enrolment for male and female learners, the distribution over the categories was not noticeably different. No significant relation between the reasons for enrolment and persistence was found.

Luik et al. [71] developed a seven-factor motivation scale for programming MOOCs called FIEM, which includes three factors related to learner expectations, three regarding learner values, and one social factor. The learner’s interest in the topic, their expectations of the course, the learner’s affinity for distance learning, and the course’s impact on family and work were deemed most influential. Usefulness concerning one’s own children, social influence, and the relevance to certification were deemed less relevant by the learners.

3.3. Engagement in MOOCs

Learner engagement has been defined in a variety of ways in different educational studies. Early educational research related to engagement often defined engagement as a one-dimensional concept. For example, McIntyre et al. [77] used the time that learners would spend on a task as a measure of engagement. Marks [74] used attention and effort as a measure of engagement instead. In more recent research, engagement is often viewed as a multidimensional concept, using a combination of two to four of the following categories: behavioural engagement, cognitive engagement, emotional engagement, and social engagement [31].

3.3.1. Types of engagement

In educational research, **behavioural engagement** is usually defined as participation in educational activities [41]. Jimerson et al. [60] state that the behavioural involvement of a learner is tied to their observable actions in an educational context. Since MOOC learners' reasons for enrolment differ from formal education (see section 3.2), traditional educational engagement metrics may be less useful. Deng et al. [31] argue that, in MOOC environments specifically, clickstreams can act as a proxy for a learner's behaviour. Behavioural engagement in MOOCs is measured in various ways in educational research, and there is no clear consensus on how it should be done. In Kizilcec et al. [65], behavioural engagement is measured on a weekly basis. They use two factors: whether a learner has viewed a lecture and completed an assessment in that week. Li & Baker [69] take a similar approach, but only considers whether a learner has viewed a lecture. Perna et al. [83] use the progression of the learners to indicate behavioural engagement. This includes the percentage of learners who accessed any lecture, the percentage of learners who accessed the first lecture, and those who accessed the last lecture. Similarly, the progression of the learners is also measured by their quiz participation: whether they attempted any quiz, attempted the first quiz, or attempted the last quiz. Additionally, achieving a final grade of 80% or above serves as a further measure of engagement.

Cognitive engagement is interpreted as the degree to which a learner grasps and learns something in a task [20]. Learners can use different cognitive strategies to complete a task [106]. In education research, cognitive behaviour is measured in a variety of ways. Shan [94] identifies multiple methods for measuring cognitive engagement. These methods include self-report scales, personal assessments of engagement; observations, offering direct insights into engagement behaviours; and interviews, providing in-depth qualitative data. Teacher ratings give an external perspective on the learners' cognitive engagement, while experience sampling captures moment-to-moment engagement levels. Eye-tracking technology offers a window into where learners focus their attention, and physiological measures reveal the body's responses to learning tasks. Log files provide a digital footprint of learner interactions with educational content, and language and content analyses offer a deep dive into the qualitative aspects of learner engagement. However, many of these methods are not applicable for measuring cognitive engagement in MOOCs. According to Sinha et al. [95], learners pausing videos is an effective indicator of higher cognitive engagement. Watch time has been used as an indicator of engagement both in MOOCs and on other platforms with video content, such as YouTube [48]. Guo et al. [48] further utilise problem attempts as an engagement indicator, defining problem attempts as a learner interacting with an assessment problem within 30 minutes after watching a video.

Emotional engagement refers to the emotional connections that learners have with other learners, educators, institutions or the content [60]. In previous educational research, emotional engagement has been measured through the degree of positive and negative feelings toward teachers, peers, academic work, or the educational institution, including their sense of belonging [42]. In MOOC research, this is often measured through the analysis of emotions in forum posts [15, 23, 70].

Finally, **social engagement** is the term used to describe social interactions in a learning environment, specifically, interactions between learners, and interactions between learners and educators. In MOOCs, those who participate in forum discussions have a higher probability of completing the course [104, 62]. Social engagement can be measured through interactions between students or between students and instructors.

3.3.2. Learner engagement trajectories

Kizilcec et al. [65] argue that a monolithic view of disengagement makes it impossible to design interventions. They argue that engagement trajectories are a more useful framework for understanding how learners interact with MOOCs, and for designing interventions. They found four prototypical engagement trajectories within three CS MOOCs. Learners in this research either had a 'Completing', 'Auditing', 'Disengaging' or 'Sampling' engagement trajectory. Firstly, a 'Completing' trajectory means that a learner has attempted the majority of assessments within a MOOC. This is most similar to a learner in traditional education. Secondly, an 'Auditing' learner instead engages with the MOOC by watching the majority of lectures, but not engaging in assessment. Thirdly, a 'Disengaging' learner has a similar pattern to 'Completing' up until a certain point, where they drop out completely or only watch some lectures. Finally, the 'Sampling' learner only watches one or two lectures throughout the course.

These four engagement trajectories account for 98% of learners in the study of Kizilcec et al. [65].

3.4. Gender differences in MOOC behaviour

Men and women exhibit different behaviours when interacting with MOOCs, which may influence their respective dropout patterns. Previous research has shown that women are more inconsistent in their time investment in each session compared to men [103] and are more likely to perform backjumps in MOOCs [49]. Backjumps are jumps back to previous material in the MOOC. These behaviours suggest differing levels of engagement, possibly indicating that women engage more deeply with the content than men. Despite these signs of active engagement, dropout rates remain high across all demographics in MOOCs, with rates as high as 90% [4, 86]. Specifically, within CS MOOCs, gender differences in dropout have been found; men are less likely to drop out than women [26, 36]. This finding is consistent with observations in university settings [63, 59].

In programming MOOCs, dropout rates are highest at the start of the course [90], with a peak in dropouts occurring just before the start of a project [90]. The dropout pattern varies between self-paced and instructor-paced MOOCs. In self-paced MOOCs, dropout typically peaks during the first assessment period, decreases in the second, and then stabilizes [87]. Contrarily, in instructor-paced MOOCs, the dropout rate is influenced by the course length. Shorter courses, lasting between 4 and 7 weeks, see a quick stabilization after the initial week [30], whereas longer courses may take about 6 weeks for the dropout rates to stabilize [79].

4
Methods

In this chapter, we outline the methods used to investigate gender differences in reasons for enrolment and engagement, and the association between these two. First, we describe the specific MOOCs selected for analysis. Next, we discuss the participants, providing insight into their demographic backgrounds. After this, an overview of the measures will be given, encompassing both the survey questions and the engagement metrics used to measure learner engagement. Finally, we outline the data analysis methods, specifying the statistical techniques and approaches applied to interpret the collected data and to answer the research questions effectively.

4.1. Materials

We analysed four different CS MOOCs offered by the Delft University of Technology (TU Delft) on the EdX[1] platform. The selection criteria result in a cross-section of popular introductory CS MOOCs. The selection criteria are:

- The topic of the MOOC must be related to CS.
- The faculty responsible for the MOOC is the Faculty of Electrical Engineering, Mathematics, and Computer Science (EEMCS) at TU Delft.
- The language of the MOOC is English.
- The target group for the MOOC is people new to CS, focused specifically on introductory courses.
- The MOOC is either the first in a sequential series of MOOCs, or a standalone MOOC.
- The MOOC has at least 500 enrolments per course run.

Of the 170 unique MOOCs that the TU Delft offers or has offered, these selection criteria left seven MOOCs. Of the remaining seven courses, the four courses with the highest enrolment were selected. This final selection can be seen in Table 4.1.

Table 4.1: Final selection of MOOCs

Course code	Course name	Total enrolments	Instructor-paced runs	Self-paced runs
EX101x	Data Analysis	71323	1	3
FP101x	Functional Programming	73191	1	0
ST1x	Automated Software Testing: Practical Skills for Java Developers	23483	2	3
UnixTx	Unix Tools: Data, Software and Production Engineering	6991	0	4

[1] https://www.edx.org

4.2. Participants

Participants in this study are anonymised learners who have participated in one or more of the four MOOCs described in section 4.1. A learner who has participated in multiple MOOCs is seen as a separate learner in each MOOC. Research question 1, which focuses on reasons for enrolment, is answered by including all learners who have filled in a self-reported pre-survey for any one of the MOOCs. Research question 2, which addresses engagement, will consider all learners who have interacted with the MOOC at least once. Finally, research question 3 only includes learners who have both filled in the pre-survey and engaged with at least one MOOC element. This research has been approved by the ethics committee at TU Delft, and a committee from the Extension School, who are responsible for TU Delft's MOOCs.

4.2.1. Gender

Within EdX, learners have the option to specify their gender identity in their profiles, choosing from "Female," "Male," or "Other." Providing this information is not mandatory. A significant number of learners opt not to disclose their gender. In Table 4.2, this group is indicated by "Unknown learners". For this research, we will focus exclusively on the data from learners who identify themselves within the two categories 'Male' and 'Female'. This is based on the scope of this research and does not intend to overlook other gender identities.

Table 4.2: Number of learners per gender per course

Course code	Male learners	Female learners	Other learners	Unknown learners
EX101x	41153	16823	279	13068
FP101x	46018	6662	440	19971
ST1x	9001	3818	94	10570
UnixTx	2970	595	39	3387

4.2.2. Age

FP101x has the youngest mean age of these four courses (see Table 4.3), while UnixTx attracts an older audience. The median is consistently lower than the mean, suggesting that there is a significant minority of older learners who participate in these MOOCs. In all four courses, female learners are younger on average than their male counterparts. UnixTx has the largest age gap; the median for women is 27, while it is 33 for men. A histogram of the ages per course can be found in section A.1.

Table 4.3: Average age, standard deviation, and median age of learners by course and gender

Course	Gender	Mean age	Std. dev.	Median
FP101x	Both	28.8	9.7	27.0
	Female	27.1	9.0	25.0
	Male	29.0	9.7	27.0
ST1x	Both	32.4	9.2	31.0
	Female	31.2	8.1	30.0
	Male	32.8	9.6	31.0
EX101x	Both	31.9	9.6	30.0
	Female	31.5	9.1	29.0
	Male	32.1	9.8	30.0
UnixTx	Both	33.6	11.0	32.0
	Female	29.9	9.6	27.0
	Male	34.3	11.1	33.0

4.2.3. Geographical location

Next to a diverse age range, the learners who participated in these MOOCs also have diverse countries of origin. Figure 4.1 shows that the US and India are in the top 5 countries with the most learners for every course. Namibia is also notably a country with many learners taking these MOOCs. For FP101x and EX101x, it is even the country with the most participants. A visualisation per course can be found in section A.2.

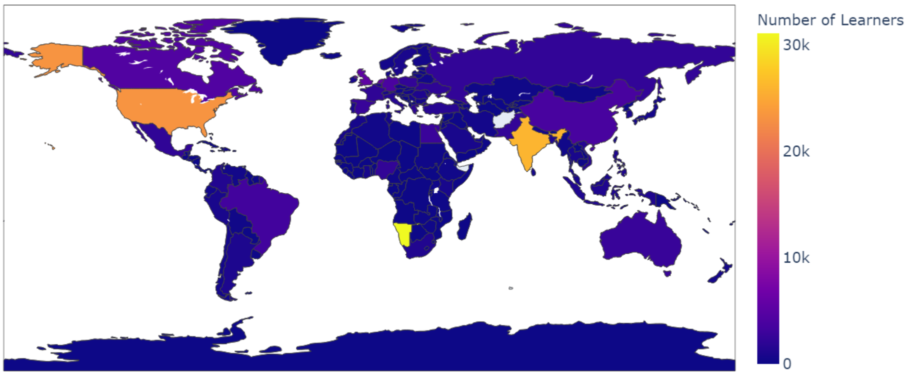


Figure 4.1: Learner location distribution of all four MOOCs combined.

4.2.4. Educational background

Across all these courses, bachelor's degrees and master's degrees are by far the most common levels of education (see section A.3). This indicates that these courses mainly attract people who already have a higher level of education. However, there are also significant numbers of learners who have just completed secondary education. This reflects the accessibility of the courses for students from different educational backgrounds. This accessibility with respect to different educational backgrounds is important for this research, as the objective is to analyse introductory CS MOOCs, meaning that a higher level of education should not be required.

4.3. Procedure

4.3.1. Reasons for enrolment

There are many reasons a learner might enrol in a MOOC. Sometimes there are different factors influencing the learner's reason for enroling in a MOOC, and sometimes there is just one reason. We will now describe how we will answer RQ1, which is about gender differences in reasons for enrolment in CS MOOCs.

At the start of the MOOCs that the TU Delft offers, the learner is asked to answer a pre-survey created by the TU Delft. It is not mandatory to complete this survey, but it gives us a better understanding of the learner which cannot be obtained purely from their demographic data and their actions within a MOOC. The pre-survey has gone through multiple iterations over the years. The phrasing of the questions relating to enrolment has changed slightly over the years, but they are still similar enough that they can be compared.

Classifying closed-ended responses

In every survey version over the years, learners are asked to pick the answer that best aligns with their motivation. Over the different versions, there are six categories that the answers relating to reasons for enrolment can fall into. These categories are as follows:

- The learner knows the instructor.
- The learner is participating, because the MOOC is related to their (prospective) career.
- The learner is participating, because the MOOC is related to their degree.
- The learner has an interest in the topic of the MOOC.

- The learner wants to teach the topic to others.
- The learner has another reason for participating.

In older pre-surveys, a learner could indicate they knew the instructor as their most important motivational reason. In more recent surveys, this answer is no longer included. Similarly, a learner can also no longer indicate they are taking the MOOC for a teaching-related reason. These reasons will still be included. The different motivation categories are mutually exclusive, as learners indicate only their most important reason for enrolment. The current phrasing of this question can be seen in Figure 4.2.

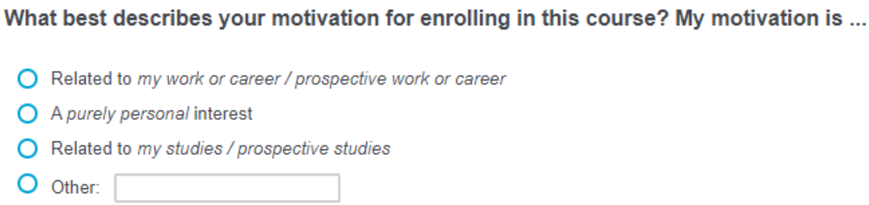


Figure 4.2: May 2024 pre-survey question for reasons of enrolment

To partly answer research question 1, we will use the statistics defined in subsection 4.3.4 to measure how associated gender and reasons for enrolment are. Only learners who filled in the pre-survey will be included in answering this research question.

Classifying open-ended responses

Within the pre-survey asked before each MOOC, a learner could always answer what their reason for enrolment was in two ways: through a closed-ended response, or through an open-ended response. To get comparable results for the closed-ended and open-ended responses, we decided that we will use the same six categories for the open-ended responses as the closed-ended responses.

For the analysis of the reasons for enrolment that learners gave for enrolling in CS MOOCs, a keyword categorisation approach will be employed instead. Since the dataset is relatively small, this approach will be combined with a manual classification to allow comparing the results of the keyword categorisation approach. This will be done by manually going through the open-ended responses to identify terms that are both common and distinctive, helping in the accurate categorisation of each response. Each response will be converted to lowercase, and punctuation and stop words will be removed. Finally, each word will be counted towards a category if it is found in the terms belonging to that category, otherwise it will be ignored. If multiple categories are equally likely, the response will be assigned to the 'Other' category. However, through manual checking of results, it was found that career-related keywords clearly distinguish the 'Career' category from other categories. Therefore, if the 'Career' category and another category have the same number of related keywords, the response will be assigned to the 'Career' category. Similar to the closed-ended responses, these categories are mutually exclusive.

Seeing as this approach is not yet validated, all responses will also be categorised manually. A comparison will be made between the automatic and manual categorisation, which will be further explained in subsection 4.3.4. This will be done by comparing each result of the automatic categorisation to the manual categorisation, and finding how high the level of agreement is between these. Since the process of labelling responses by hand is quite time-consuming, an automatic system to label what category responses fall into would make it much more efficient to get insights into why learners are taking part in a course. To fully answer research question 1, we will also compare the manually labelled open-ended responses between men and women similarly to the closed-ended responses.

4.3.2. Behavioural engagement

Before we can measure learner's behavioural engagement, we first need to process the data from the four MOOCs into a more manageable form.

Processing MOOC data

The data delivery from the selected MOOCs has two types of data: on the one hand, there is a large amount of log data generated by the learner's actions. The log data consists of all types of interactions that learners have with the MOOCs. On the other hand, there is metadata that describes the course and its learners. Analysing the data in its raw, textual format poses many challenges. It is slow and difficult to analyse, as querying specific information and performing joins across different data sources becomes cumbersome and inefficient. To analyse the fourteen MOOC runs across four different MOOCs effectively, a database was created from the log data and metadata. This database was largely based on the implementation of ELAT[2], but there are some key differences. This MOOC database is implemented in JavaScript with Node.js and produces a MongoDB that can be used for further analysis.

The course codes (which are ‘EX101x’, ‘FP101x’, ‘UnixTx’ and ‘ST1x’ in this research) can be configured in the processing of course data. This automatically detects all course runs within a specified directory and builds the database from all detected course runs. With the current ELAT implementation, it is only possible to create a database from a single course run, which makes it a lot more difficult to do a larger analysis over multiple course runs. The created database can be used for more analyses of EdX MOOC data, as long as all the required files are available. A brief, technical implementation will now be described.

Metadata

The course structure file is first parsed. From this file, useful information can be extracted about the course. It includes the course identifier, the course name, and the course’s start and end date. Furthermore, it also includes the course structure. This describes how elements are ordered, their hierarchy, and when they are due.

Log data

Log data processing is almost unchanged from the original implementation of ELAT [99]. All detected log files for a course are processed by several functions, which extract information that can be useful for analysing the behaviour of MOOC learners is a variety of ways. These functions extract:

1. General sessions: Information about EdX sessions.
2. Video interaction sessions: Sessions and information about interactions with videos, such as number of pauses or times a learner skipped forwards or backwards in the content.
3. Assessment submissions: Information about the final score and submissions of a learner for an assessment.
4. Quiz sessions: The start and end time, and duration of a learner’s quiz session.
5. ORA sessions: Information about a learner’s interaction with an ORA element, such as if the element is self-assessed, how many times they saved it, and the start and end time.
6. Forum sessions: Information about the learner’s forum activity,

This database of metadata and log data can be constructed for any selection of EdX MOOCs, as long as EdX data packages[3] are available. Therefore, it can be used for further research with EdX MOOCs.

Measuring behavioural engagement

To describe learner behaviour over the entire MOOC, we will use the concept of learner trajectories and a methodology inspired by Kizilcec et al. [65]. Since the original research focuses on only one course with a deadline, and not every MOOC run in our dataset has deadlines, we will have to adjust the approach slightly.

First, we describe how to measure learner behaviour for MOOC runs with deadlines, which are the instructor-paced MOOCs. For each assessment period, we start by finding the elements that are due during that assessment period. For quizzes, problems, or open response assessments (ORAs) due during a week, they get one of five labels.

1. On track (T) if they completed all elements due in the assessment period on time.
2. Behind (B) if they completed all elements of that type due in the assessment period throughout the course, but some were handed in late.

[2] `https://github.com/mvallet91/ELAT-Workbench`
[3] `https://edx.readthedocs.io/projects/devdata/en/latest/`

3. Auditing (A) if they completed any element of that type due in the assessment period throughout the course.
4. Out (O) if they completed no element of that type throughout the course.
5. No elements due (X) if there are no elements of that type due during the assessment period.

Since videos do not require as much effort to participate in compared to the others, a learner gets either an A, O, or X for videos for every assessment period.

Course runs without deadlines, namely the self-paced runs, do not have the concept of being behind, since it is impossible to be behind if there are no deadlines. If a learner completed all elements of a type in a single assessment period, they would always be “on track” for that period. In self-paced MOOCs, the element types quiz, problem and ORA get one of the four labels $[T, A, O, X]$. The labels have the same values as instructor-paced runs, so $[3, 1, 0, 0]$ respectively. Learners still get a score of $A(1))$ for video engagement in an assessment period if they have watched a video from that period.

If we take quiz participation as an example, a learner's engagement over a whole MOOC may look like this: $[T, T, B, A, O, X]$. The learner would be on track for the first two periods, meaning they completed all quizzes. For the next period, they would have completed all quizzes, but completed some of them late. In the next period, they would have completed some of the quizzes for that period, but not all of them. In the next period, they did not complete any quizzes. In the final period, there is no quiz. The X makes it easier to determine whether a learner did not engage with the material or if there was no material to engage with, but it does not change the learner's score. The label X is used to determine if there are any elements due during an assessment period. If there are no elements due, the assessment period is skipped.

To compare between learners' engagement, we calculate the L_1 norm for each assessment period by adding up the quiz engagement, problem engagement, ORA engagement, and video engagement for each learner. Using the same engagement to numerical value mapping as Kizilcec et al. [65], namely $T = 3$, $B = 2$, $A = 1$ and $O = 0$ (and in our case, $X = 0$ as well), the maximum engagement score for an assessment period falls in the boundary $[0, 10]$ and a learner's engagement score for that assessment period falls in the boundary $[0, \texttt{max\_score}]$. An example of this can be seen in Table 4.4.

Table 4.4: Example of a learner's engagement score per assessment period

Assessment period	1	2	3	4	5	6
Quiz engagement	T (3)	T (3)	B (2)	A (1)	O (0)	X (0)
ORA engagement	T (1)	B (2)	T (3)	O (0)	X (0)	X (0)
Submission engagement	B (2)	A (1)	A (1)	T (3)	T (3)	O (0)
Video engagement	A (1)	O (0)	A (1)	X (0)	X (0)	X (0)
Score	7	6	7	4	3	0
Max score	10	10	10	9	6	3

In the end, each learner will have an engagement score for every assessment period. Based on these values, we will perform the k-means clustering algorithm 100 times for each course run, as was done in Kizilcec et al. [65]. We initialise the algorithm with 4 clusters (see subsection 3.3.2). Because k-means clustering starts with random cluster centroid assignments, each run of the algorithm will be different. Out of all runs, we take the clustering result with the highest silhouette score (i.e., the result where the learners are matched best with the four resulting clusters).

Research question 2 relies on learners' engagement with the MOOC. The research question will be answered by calculating the statistical tests from subsection 4.3.4 using gender and the cluster that the learner falls in as variables. This will be done for each course separately, and also adding all courses together.

4.3.3. Association between reasons for enrolment and behavioural engagement

For research question 3, we will only look at the association between the closed-ended responses and the behavioural engagement for the learners. The analysis of the open-ended responses is not validated with the learners who originally gave the response, which means these results should not be combined with the responses to the closed-ended question. For this research question, only learners who have completed the pre-survey and have interacted with one of the four MOOCs at least once will be included. The categorisation of the learners' reasons for enrolment and their behavioural engagement from the previous research questions will be used. After calculating the statistical tests from subsection 4.3.4 for men and women separately, we can conclude to what extent reasons for enrolment influence behavioural engagement in introductory CS MOOCs.

4.3.4. Statistical tests

In this section, we will describe any statistical tests used to interpret the results.

Association for nominal variables

To see if there is any association between a learner's gender, reason for enrolment in the MOOC, and behavioural engagement, we will make use of three statistical tests: the χ^2 test, Cramér's V test, and Cohen's ω. These three tests can be used to show the significance and effect size of the association between two nominal variables, which are variables that are divided into at least two categories, but have no intrinsic ordering.

The χ^2 test is a statistical method used to determine the independence of two categorical variables by comparing the observed frequencies in the data to the frequencies that would be expected if the variables were independent. It does this by comparing the observed results in a contingency table with the frequencies if the variables were independent. The `chi2_contingency` function from `scipy` is used for calculating this. For each comparison, the χ^2 test provides a χ^2 statistic and a p-value. A low p-value indicates that there is a significant association between the variables. In the case of this research, we will use $p < 0.05$ as a significant result.

While the χ^2 test determines whether two categorical variables are significantly associated, we also need to find the effect size. Cramér's V [25] shows us how strongly the two variables are associated. It results in a value between 0 and 1, where 0 indicates a weak association, and 1 indicates a strong association. We use `association` from `scipy` to calculate Cramér's V.

Cohen's ω indicates the effect size of the association between two nominal variables, similarly to Cramér's V. However, the association between the variables uses Cohen's interpretation instead. This interpretation is commonly used in behavioural science [22]. ω is calculated with the following formula:

$$\omega = V\sqrt{min(r,k) - 1}$$

where V is the result from Cramér's V, and r and k are the rows and columns of the contingency table. Cohen's interpretation of Cohen's ω [22] is given in Table 4.5. We used our own implementation of Cohen's ω, since no implementation was available.

Table 4.5: Effect size interpretation for Cohen's ω values, adapted from Cohen [22].

ω	Effect Size
$<$ 0.10	Negligible
0.10–0.30	Small
0.30–0.50	Medium
$>$ 0.50	Large

Cohen's Kappa

In Figure 4.3.1, a system for automatically labelling what category an open-ended response to the question of why a learner enrolled in the MOOC will be described. To measure how well a system like this works, the responses will also be labelled by hand. For comparing the automatically and manually categorised responses, we will use Cohen's κ, which measures the agreement between two raters (i.e., the automatically and manually labelled responses). We use `cohen_kappa_score` from `sklearn` as the implementation.

κ can range from -1 to 1. An interpretation of Cohen's κ from Landis & Koch [68] is given in Table 4.6.

Table 4.6: Interpretation of Cohen's κ for the strength of agreement, adapted from Landis & Koch [68].

κ	Strength of Agreement
$<$ 0.00	Poor
0.00–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Almost Perfect

5

Results

This section presents the findings of the study, organised into three main areas: reasons for enrolment, behavioural engagement, and the association between these two factors. Firstly, we analyse the reasons for enrolment using both closed-ended and open-ended responses, highlighting the key motivations for learners. Next, we examine behavioural engagement, categorising the different patterns of interaction with the MOOCs. Finally, we explore the association between reasons for enrolment and engagement, assessing how initial motivations correlate with subsequent engagement levels.

5.1. Reasons for enrolment

Since the classification of the closed-ended responses and open-ended responses is performed with different approaches, the results will also be shown separately.

5.1.1. Closed-ended responses

The closed-ended responses were divided into six different categories as described in subsection 4.3.1.

Table 5.1: Number and percentage of responses in each of the derived categories of reasons for enrolling in the courses, divided by gender

		Course				
		EX101x	FP101x	ST1x	UnixTx	Total
Men	Career	3301 (71.74%)	930 (38.24%)	1047 (76.15%)	238 (58.77%)	5516 (61.82%)
	Interest	1013 (22.02%)	1263 (51.93%)	162 (11.78%)	94 (23.21%)	2532 (28.40%)
	Degree	234 (5.08%)	71 (2.92%)	126 (9.16%)	66 (16.28%)	497 (5.57%)
	Other	42 (0.91%)	39 (1.60%)	7 (0.51%)	7 (1.73%)	95 (1.06%)
	Teaching	41 (0.89%)	-	33 (2.40%)	3 (0.74%)	77 (0.86%)
	Know the Instructor	10 (0.22%)	129 (5.30%)	-	-	139 (1.56%)
	Total Men	4641	2432	1375	408	8856
Women	Career	1641 (79.23%)	64 (38.32%)	560 (81.28%)	55 (67.90%)	2320 (71.26%)
	Interest	308 (14.87%)	91 (54.49%)	64 (9.30%)	7 (8.64%)	470 (14.43%)
	Degree	96 (4.63%)	9 (5.39%)	59 (8.57%)	18 (22.22%)	182 (5.59%)
	Other	24 (1.15%)	2 (1.20%)	6 (0.87%)	1 (1.23%)	33 (1.01%)
	Teaching	15 (0.72%)	-	13 (1.89%)	4 (4.94%)	32 (0.98%)
	Know the Instructor	2 (0.10%)	1 (0.60%)	-	-	3 (0.09%)
	Total Women	2086	167	702	85	3040

Note: The reasons for enrolment for a single course add up to $\approx 100\%$ for each gender.

Table 5.1 shows the results of the categorisation of all the responses to the closed-ended question about reasons for enrolment from all MOOC runs together, organised per MOOC. Within these courses, women are generally more likely to enrol for career-related reasons compared to men as can be seen in Figure 5.2. This trend can be seen particularly in EX101x (Figure 5.1a), ST1x (Figure 5.1c), and UnixTx (Figure 5.1d). These graphs show the comparative odds ratios with 95% confidence intervals for reasons for enrolment given by men and women for the four MOOCs, and all four MOOCs combined. Subplots are added in Figure 5.1 and Figure 5.2 for readability. Interest in the topic of the MOOC is also a popular reason. Women are more inclined to enrol in FP101x out of interest compared to men. Conversely, men show a higher interest in EX101x and UnixTx. In terms of enrolling for reasons related to the learner's degree, UnixTx stands out. For both men and women, a much higher percentage enrolled in this MOOC for degree-related reasons. Teaching-related motivations show a gender difference in UnixTx, where 4.94% of women enrolled for teaching purposes compared to 0.74% of men. Finally, knowing the instructor is a more significant factor for men in FP101x, where 5.30% of men enrolled for this reason, compared to 0.60% of women.

The χ^2, Cramér's V and Cohen's ω tests were applied to each course individually to determine if there were significant differences between men and women in their enrolment reasons. Not every reason for enrolment was available for every course in the multiple-choice question. These clusters were removed to be able to calculate the statistical tests. The results in Table 5.2 indicate significant gender-specific differences in enrolment motivations for all the courses analysed. Cohen's ω for FP101x indicates a high association between gender and the reasons for enrolment. For UnixTx, there was a medium-strength association between gender and reasons for enrolment. EX101x has a low-medium association strength, and finally, ST1x has a weak strength. Combining the reasons for enrolment for women and women across all courses, we also found a significant difference between the reasons for enrolment of women and men, with a medium effect size.

Table 5.2: χ^2, p-value, Cramér's V, and Cohen's ω for each course, indicating the strength of association between gender and reasons for enrolling

Course	χ^2	p-value	Cramér's V	Cohen's ω
EX101x	82.48	1.63×10^{-16}	0.111	0.222
FP101x	258.28	2.40×10^{-54}	0.315	0.546
ST1x	13.52	0.018	0.081	0.140
UnixTx	19.23	0.0017	0.198	0.343
All courses	264.65	3.94×10^{-55}	0.149	0.298

5.1.2. Open-ended responses

Table 5.3 shows the manual labelling of the open-ended text responses to the 'reasons for enrolment' question. While there are relatively few responses compared to the closed-ended question, we can see some similar trends. For example, for FP101x, the largest group of the respondents is taking the course out of interest. For the ST1x course, the largest group of men and women is taking the course because of their (prospective) career. Similarly, the majority of men who answered this question for UnixTx are taking the course because of their career, while for women, the responses are more spread out over the categories.

The automatic labelling of the responses can be seen in Table 5.4. We can see that the automatically labelled categories do differ from the manually labelled ones. The automatic labelling system mainly misses responses to the 'Career' and 'Interest' categories, while labelling too many responses as falling in the 'Degree' and 'Other' categories.

To understand how well the labelling from the automatic clustering system corresponds with the manual labelling, we will use the approach described in subsection 4.3.1. From the manually and automatically labelled responses, we can calculate Cohen's κ, which can be seen in Table 5.5. Using the interpretation for Cohen's κ found in Table 4.6, there is a 'Moderate' agreement between the two systems in the EX101x course. For FP101x, the strength of agreement is lower, falling in the middle of 'Fair'. For ST1x, the strength of agreement is in the higher range of 'Fair'. The strength of agreement in UnixTx is the highest out of the four courses, falling in the middle 'Moderate'. Over all responses, the two systems had an agreement in the lower range of 'Moderate'.

We can now answer the first research question. There are significant differences in reasons for enrol-

Table 5.3: Manual labelling of open-ended reasons for enrolment responses for each course and gender

		Course				
		EX101x	FP101x	ST1x	UnixTx	Total
Men	Career	0 (0.00%)	6 (15.79%)	43 (67.19%)	12 (75.00%)	61 (48.41%)
	Interest	1 (12.50%)	17 (44.74%)	15 (23.44%)	3 (18.75%)	36 (28.57%)
	Degree	1 (12.50%)	7 (18.42%)	2 (3.13%)	0 (0.00%)	10 (7.94%)
	Other	6 (75.00%)	6 (15.79%)	3 (4.69%)	1 (6.25%)	16 (12.70%)
	Teaching	0 (0.00%)	2 (5.26%)	0 (0.00%)	0 (0.00%)	2 (1.59%)
	Know the Instructor	0 (0.00%)	0 (0.00%)	1 (1.56%)	0 (0.00%)	1 (0.79%)
	Total Men	8	38	64	16	126
Women	Career	1 (25.00%)	0 (0.00%)	39 (76.47%)	1 (25.00%)	41 (67.21%)
	Interest	2 (50.00%)	2 (100.00%)	7 (13.73%)	1 (25.00%)	12 (19.67%)
	Degree	0 (0.00%)	0 (0.00%)	1 (1.96%)	1 (25.00%)	2 (3.28%)
	Other	1 (25.00%)	0 (0.00%)	2 (3.92%)	1 (25.00%)	4 (6.56%)
	Teaching	0 (0.00%)	0 (0.00%)	2 (3.92%)	0 (0.00%)	2 (3.28%)
	Know the Instructor	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
	Total Women	4	2	51	4	61

Note: The reasons for enrolment for a single course add up to $\approx 100\%$ for each gender.

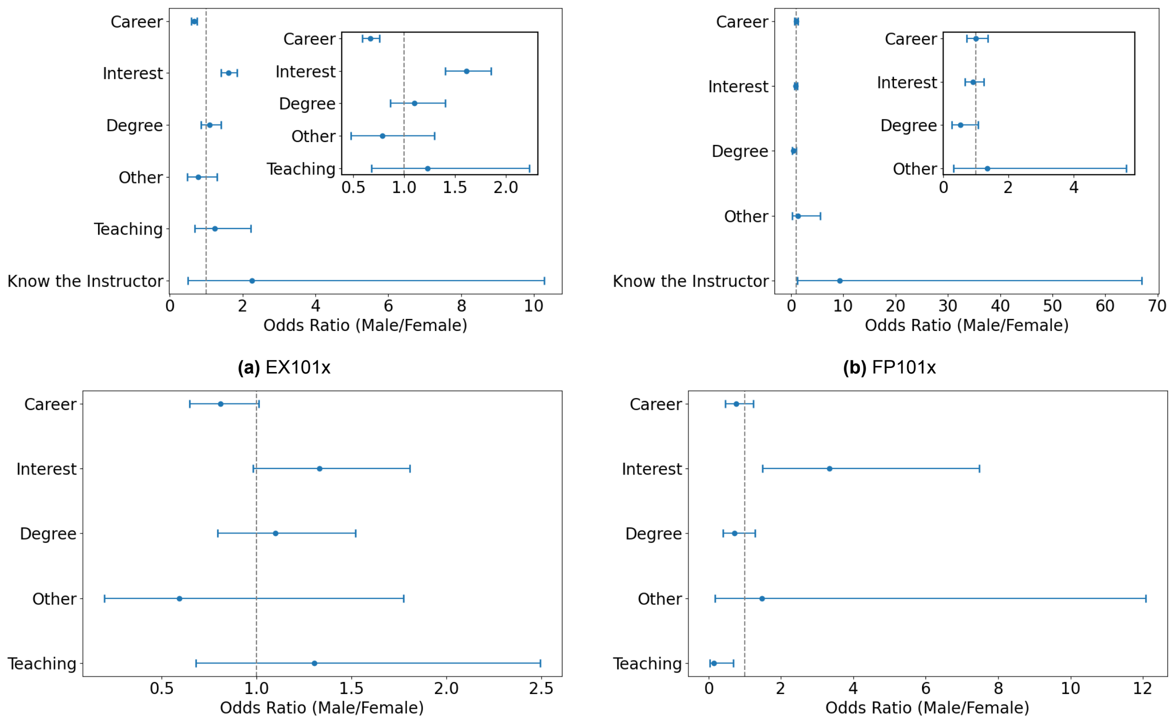
Table 5.4: Automated labelling of open-ended reasons for enrolment responses for each course and gender

		Course				
		EX101x	FP101x	ST1x	UnixTx	Total
Men	Career	0 (0.00%)	6 (15.79%)	37 (57.81%)	10 (62.50%)	53 (42.06%)
	Interest	3 (37.50%)	5 (13.16%)	4 (6.25%)	1 (6.25%)	13 (10.32%)
	Degree	1 (12.50%)	18 (47.37%)	4 (6.25%)	1 (6.25%)	24 (19.05%)
	Other	4 (50.00%)	8 (21.05%)	19 (29.69%)	4 (25.00%)	35 (27.78%)
	Teaching	0 (0.00%)	2 (5.26%)	0 (0.00%)	0 (0.00%)	2 (1.59%)
	Know the Instructor	0 (0.00%)	0 (0.00%)	1 (1.56%)	0 (0.00%)	1 (0.79%)
	Total Men	8	38	64	16	126
Women	Career	1 (25.00%)	0 (0.00%)	32 (62.75%)	1 (25.00%)	34 (55.74%)
	Interest	0 (0.00%)	0 (0.00%)	4 (7.84%)	0 (0.00%)	4 (6.56%)
	Degree	0 (0.00%)	2 (100.00%)	4 (7.84%)	1 (25.00%)	6 (9.84%)
	Other	3 (75.00%)	0 (0.00%)	11 (21.57%)	2 (50.00%)	16 (26.23%)
	Teaching	0 (0.00%)	0 (0.00%)	0 (0.00%)	1 (25.00%)	1 (1.64%)
	Know the Instructor	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
	Total Women	4	2	51	4	61

Note: The reasons for enrolment for a single course add up to $\approx 100\%$ for each gender.

Table 5.5: Cohen's κ values for agreement between automated and manual labelling of open-ended responses for each course

Course	Cohen's κ
EX101x	0.429
FP101x	0.283
ST1x	0.347
UnixTx	0.510
All courses	0.424



(a) EX101x **(b)** FP101x **(c)** ST1x **(d)** UnixTx

Figure 5.1: Male/Female odds ratios for reasons for enrolment across four different MOOCs

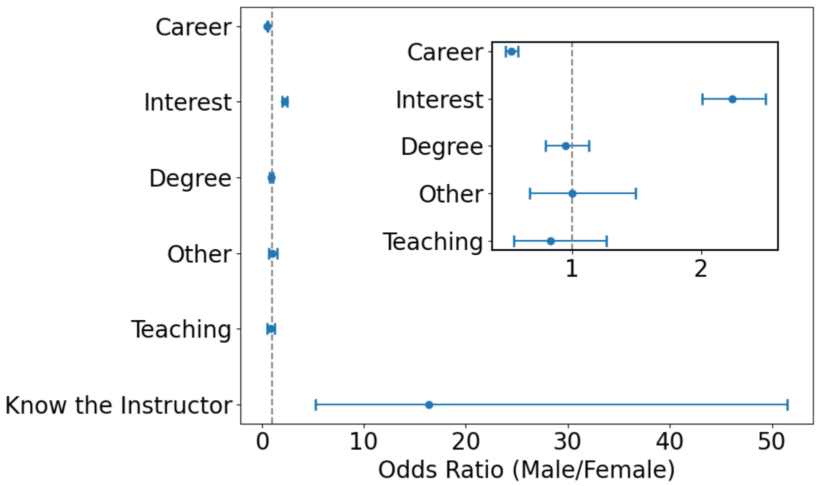


Figure 5.2: Male/Female odds ratios with 95% CI for reasons for enrolment with all courses combined

ment between men and women, but the three most common categories are the same. These categories of reasons for enrolment are career-related, interest-related, and degree-related, in that order for both men and women. Women enrol in introductory CS MOOCs more often for career-related reasons than men, while men enrol more often because of interest-related reasons than women.

5.2. Behavioural engagement

We will now show the results from the methodology described in item 4.3.2. In Figure 5.3, we can see an example of the engagement levels over each assessment period within the MOOC. The black line on top indicates the maximum score possible for that week, and the four other lines show the centroids for the four different clusters 'Completing', 'Auditing', 'Disengaging' and 'Sampling'. A graph like this can be generated for each course run, giving course designers insight into where learners are less engaged within a course run.

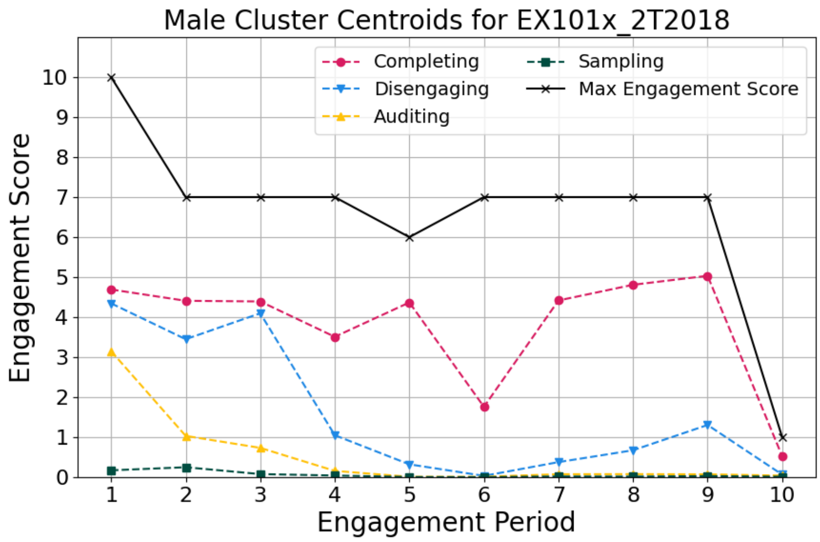


Figure 5.3: Learning trajectories of male learners in a run of EX101x

In this research, however, we will just be comparing the engagement levels between men and women for each MOOC. Table 5.6 shows the learner trajectory clusters that male and female learners fall into for each course. Only a small group of learners for both men and women fell into the 'Disengaging' cluster, which are learners who start engaging with the material like the 'Completing' cluster, but end up having decreased engagement at some point in the course. The 'Completing' cluster, the learners who interacted with the majority of the course, was slightly smaller than the 'Disengaging' cluster. The 'Auditing' cluster was larger than the previous two. Notably, the percentage of learners falling into this cluster for both men and women is much higher than for the other courses, representing roughly one in five learners. Finally, for both men and women across all courses, the majority of learners fall into the 'Sampling' category, meaning they just interacted with a few videos at the beginning of the course. When combining all courses, women were better represented in this group compared to men.

Table 5.6: Total number and percentage of learners in each behavioural cluster for each course, divided by gender

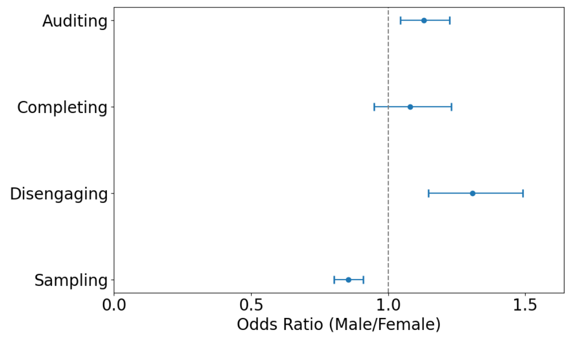
		Cluster				
		Disengaging	Completing	Auditing	Sampling	Total
Men	EX101x	961 (3.23%)	865 (2.91%)	2557 (8.60%)	25338 (85.26%)	29721
	FP101x	627 (4.32%)	734 (5.05%)	1402 (9.65%)	11761 (81.00%)	14524
	ST1x	285 (7.51%)	105 (2.77%)	428 (11.28%)	2976 (78.45%)	3794
	UnixTx	100 (5.07%)	94 (4.77%)	436 (22.11%)	1342 (68.05%)	1972
	Total Men	1973 (3.94%)	1798 (3.59%)	4823 (9.65%)	41417 (82.82%)	50011
Women	EX101x	297 (2.49%)	322 (2.70%)	916 (7.69%)	10382 (87.11%)	11917
	FP101x	23 (1.26%)	29 (1.59%)	79 (4.33%)	1694 (92.82%)	1825
	ST1x	116 (6.96%)	29 (1.74%)	183 (10.99%)	1338 (80.31%)	1666
	UnixTx	21 (4.70%)	13 (2.91%)	87 (19.46%)	326 (72.93%)	447
	Total Women	457 (2.88%)	393 (2.48%)	1265 (7.98%)	13740 (86.65%)	15855

Note: Row-wise percentages add up to $\approx 100\%$

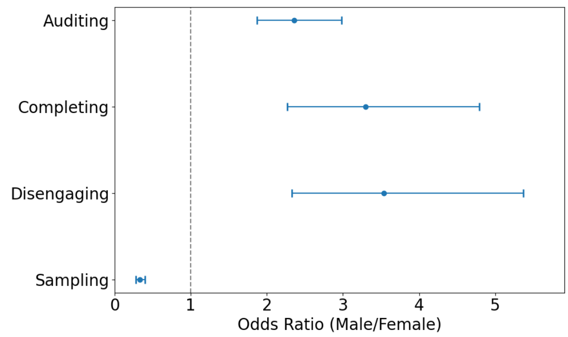
Once again, as noted in item 4.3.2, we use the statistical tests described in subsection 4.3.4. We also calculated the silhouette score for every course run, which is averaged over all course runs from one course. The results of these statistical tests can be found in Table 5.7. The silhouette scores for all courses is high, suggesting that the learners for each course are well-clustered. Since for every course, the p-value is below 0.05, we can say there is a significant association between gender and the behavioural engagement clusters that learners fall into. Turning to the interpretation of Cohen's ω from Table 4.5 again, we can say that, for the courses EX101x and FP101x, there is an effect size in the high range of medium. In ST1x, there is a large association between gender and engagement. Gender and engagement have a weak to medium association in UnixTx. When adding up the clusters for all courses, gender and engagement have a medium to high association.

Table 5.7: Average silhouette score, χ^2, p-value, Cramér's V, and Cohen's ω for each course

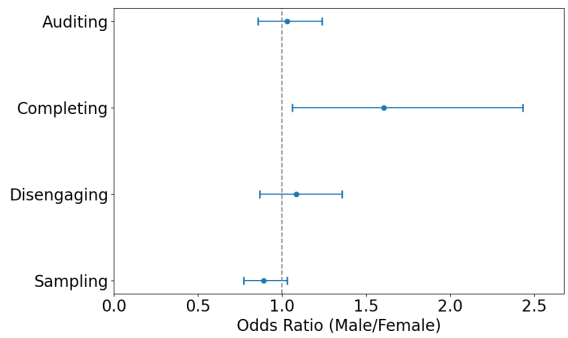
Course	Average Silhouette Score	χ^2	p-value	Cramér's V	Cohen's ω
EX101x	0.745	402.54	1.19×10^{-86}	0.316	0.447
FP101x	0.853	137.08	1.86×10^{-29}	0.305	0.431
ST1x	0.865	90.37	2.12×10^{-19}	0.478	0.676
UnixTx	0.811	22.88	0.0001	0.192	0.272
Total		651.68	2.85×10^{-137}	0.326	0.461



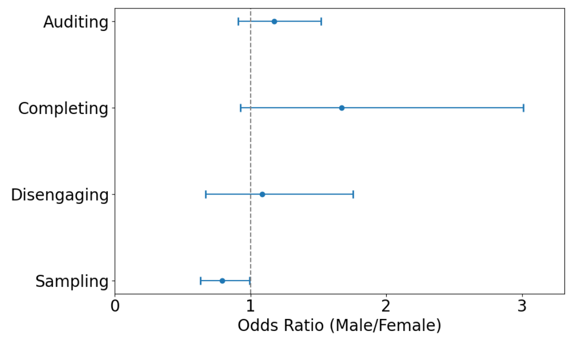
(a) EX101x



(b) FP101x



(c) ST1x



(d) UnixTx

Figure 5.4: Male/Female odds ratios with 95% CI for behavioural engagement clusters across four different courses

Figure 5.4 presents the male-to-female odds ratios for behavioural engagement clusters across four different courses: EX101x, FP101x, ST1x, and UnixTx. Each subfigure (a)-(d) illustrates the comparative odds ratios with 95% confidence intervals for the 'Auditing', 'Completing', 'Disengaging', and 'Sampling' clusters. In EX101x (Figure 5.4a), the odds ratios indicate a slight gender imbalance across different engagement clusters. The 'Auditing' cluster shows an odds ratio slightly above 1, suggesting that males are marginally more likely to fall into this cluster than females. For the 'Completing' and 'Disengaging' clusters, the odds ratios are below 1, indicating a higher proportion of females in these clusters compared to males. The 'Sampling' cluster has an odds ratio significantly below 1, showing a much higher likelihood for females to be a part of this cluster compared to to males. The odds ratios for FP101x (Figure 5.4b) reveal more pronounced differences. The 'Auditing' cluster has an odds ratio significantly above 1, demonstrating that males are substantially more likely to be in this cluster than females. The

'Completing' and 'Disengaging' clusters also show higher odds ratios for males, with the 'Completing' cluster having an odds ratio greater than 3, highlighting a notable gender disparity favouring male engagement. The 'Sampling' cluster is very close to 1, indicating a balanced gender distribution. In ST1x (Figure A.11), the 'Auditing' cluster shows a significant gender disparity with males being more likely to audit the course than females, as evidenced by an odds ratio well above 1. The 'Completing' cluster also favours males with an odds ratio around 1.5. The 'Disengaging' and 'Sampling' clusters, however, have odds ratios below 1, indicating that females are more likely to fall into these clusters than males. For UnixTx (Figure 5.4d), the pattern is similar. The 'Auditing' and 'Completing' clusters both show higher odds ratios for males, indicating a greater likelihood for males to engage in these ways. The 'Disengaging' cluster, with an odds ratio above 1, also suggests that males are more likely to disengage compared to females. The 'Sampling' cluster, with an odds ratio below 1, indicates a higher likelihood for females to engage in this manner compared to males.

Overall, the figures demonstrate that there are gender differences in behavioural engagement across these courses, with men generally more likely to be found in the 'Auditing', 'Completing', and 'Disengaging' clusters, and women are more likely to appear in the 'Sampling' cluster.

Figure 5.5 shows the combined odds ratios for all courses. The 'Auditing' cluster shows an odds ratio of roughly 1.2, indicating an almost equal likelihood for males and females to audit courses. The 'Completing' and 'Disengaging' clusters have odds ratios slightly above 1, suggesting a marginally higher likelihood for men to fall into these clusters compared to women. The 'Sampling' cluster has an odds ratio significantly below 1, indicating a higher likelihood that women only interact with a few lectures.

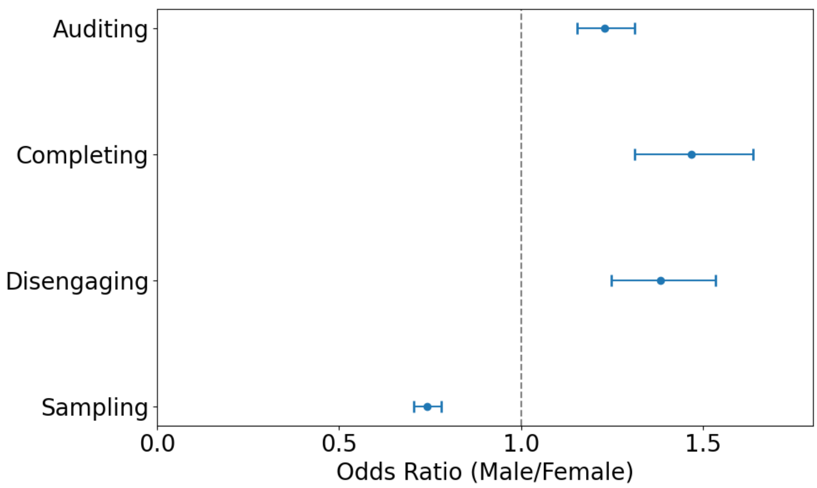


Figure 5.5: Male/Female odds ratios for behavioural engagement clusters with all courses combined

We can now answer the second research question. Women are more likely to fall into the lowest engagement cluster, 'Sampling', while men are more likely to fall into the other engagement clusters. Women, therefore, are more likely to only watch a few lectures, while men generally are more engaged through the entire MOOC. Men are also more likely to finish introductory CS MOOCs than women.

5.3. Association between reasons for enrolment and behavioural engagement

Finally, we looked at the association between reasons for enrolment and engagement for men and women. In some courses, there were too few learners who filled in both the pre-survey and interacted with the course, which would lead to a high margin of error. Therefore, it was decided to only run a statistical test on the combined clustering results and survey responses over all courses. The data for individual courses can be found in Appendix B. Table 5.8 shows the behavioural engagement clustering for men and women across different reasons for enrolment, categorised into the four engagement clusters.

For men, the largest engagement cluster is ‘Sampling’ (41.52%). For most reasons of enrolment, this cluster represents roughly 40% of learners. For the ‘Know the Instructor’ reason, relatively fewer learners fall into this cluster (25.44%). The ‘Auditing’ cluster is the second most common for men (25.26%). The learners with a reason related to teaching fall into this cluster more commonly, while fewer learners in the ‘Other’ category fall into this cluster. The ‘Disengaging’ and ‘Completing’ clusters have lower overall proportions, with ‘Completing’ being somewhat higher for ’Know the Instructor’ (31.58%).

For women, the largest cluster is also ‘Sampling’ with 54.14%, which is significantly higher than the percentage of male learners in this cluster. The ‘Auditing’ cluster follows (25.22%), The ‘Disengaging’ and ‘Completing’ clusters are once again lower with notably fewer women in the ‘Completing’ cluster.

Table 5.9 provides the results of the statistical tests from subsection 4.3.4, which examine the association between reasons for enrolment and behavioural engagement clusters for both men and women. For men, there is a significant association between reasons for enrolment and engagement ($p = 0.0011$). However, this is not the case for women $p = 0.6252$. For both genders, Cohen’s ω is lower than 0.1 (0.0766 and 0.0796 for men and women respectively), suggesting a minimal association between reasons for enrolment and behavioural engagement. The answer to the third research question is therefore that reasons for enrolment have little influence on behavioural engagement.

Table 5.8: Behavioural engagement clustering for men and women for all courses combined, divided per reason of enrolment

		Cluster				
		Disengaging	Completing	Auditing	Sampling	Total
Men	Career	609 (15.76%)	669 (17.31%)	946 (24.48%)	1641 (42.46%)	3865
	Degree	41 (13.90%)	44 (14.92%)	84 (28.47%)	126 (42.71%)	295
	Interest	279 (13.89%)	386 (19.22%)	532 (26.49%)	811 (40.39%)	2008
	Know the Instructor	21 (18.42%)	36 (31.58%)	28 (24.56%)	29 (25.44%)	114
	Other	15 (22.06%)	10 (14.71%)	12 (17.65%)	31 (45.59%)	68
	Teaching	4 (14.81%)	4 (14.81%)	9 (33.33%)	10 (37.04%)	27
	Total Men	969 (15.20%)	1149 (18.01%)	1611 (25.26%)	2648 (41.52%)	6377
Women	Career	193 (12.64%)	119 (7.79%)	397 (26.00%)	818 (53.57%)	1527
	Degree	12 (12.63%)	11 (11.58%)	26 (27.37%)	46 (48.42%)	95
	Interest	38 (11.05%)	34 (9.88%)	74 (21.51%)	198 (57.56%)	344
	Know the Instructor	0 (0.00%)	1 (25.00%)	0 (0.00%)	3 (75.00%)	4
	Other	3 (11.54%)	1 (3.85%)	6 (23.08%)	16 (61.54%)	26
	Teaching	2 (20.00%)	0 (0.00%)	3 (30.00%)	5 (50.00%)	10
	Total Women	248 (12.36%)	166 (8.28%)	506 (25.22%)	1086 (54.14%)	2006

Note: Row-wise percentages add up to $\approx 100\%$

Table 5.9: Results of Chi-Square Test, Cramér’s V, and Cohen’s ω testing the association between reasons for enrolment and behavioural engagement cluster for men and women

	χ^2	p-value	Cramér’s V	Cohen’s ω
Men	37.40	0.0011	0.0442	0.0766
Women	12.70	0.6252	0.0459	0.0796

6
Discussion

This chapter discusses the key findings of the study, which examined the relationships between gender, enrolment motivations, and engagement in introductory computer science (CS) MOOCs. It interprets the gender differences in enrolment reasons and engagement patterns, exploring their implications for improving learner engagement and retention. The chapter also acknowledges the study's limitations and suggests directions for future research.

6.1. Summary of findings

The aim of this study was to explore the association between gender, reasons for enrolment, and behavioural engagement in introductory CS MOOCs.

6.1.1. Association between gender and reasons for enrolment

The closed-ended question response analysis reveals significant gender differences in enrolment motivations across the four courses (EX101x, FP101x, ST1x, and UnixTx). For both men and women, the three most common reasons for enrolment were career-related, interest-related and degree-related, in that order. There is a medium effect size between gender and reasons for enrolment.

The open-ended question response analysis shows a similar trend, where the reasons given are still most commonly related to the learner's (future) career or the learner's interest in the topic. A reason related to a learner's degree was not named as commonly as in the closed-ended question responses. The automatic response analysis system and the manually labelled reasons for enrolment had a moderate strength of agreement.

6.1.2. Association between gender and engagement

Our analysis reveals distinct patterns of engagement between men and women in various MOOCs. The majority of both men and women fall into the 'Sampling' cluster. This reveals a tendency to engage with only a few course elements. Women are more prominently represented in this cluster compared to men. For men, the 'Auditing' cluster is notably larger, especially in FP101x, where this cluster includes approximately one in five learners. Men also have a higher presence in the 'Disengaging' cluster. Conversely, women are more frequently found in the 'Completing' cluster, suggesting more consistent engagement.

For each course, there was a significant association between gender and engagement. In the different courses, there was either a low or medium effect size. Combining the results from the four MOOCs, there is a significant association between gender and engagement, with a medium effect size.

6.1.3. Association between gender, reasons for enrolment and engagement

Finally, we investigated the association between the reasons for enrolment and engagement clusters for men and women. The learners from this question, who filled in both the pre-survey and engaged with the MOOC, are more engaged compared to the previous research question, where we considered all learners who interacted with the MOOC. We found that for men, there is a significant, but negligible association between reason for enrolment and engagement. For women, there was no significant association.

6.2. Interpretation of results

The findings of our study reveal significant gender-specific patterns in the reasons for enrolment and engagement behaviours in MOOCs. These insights provide a deeper understanding of learner behaviour in online education and suggest areas for targeted interventions to improve engagement and retention.

6.2.1. Gender and reasons for enrolment

The analysis of the reasons for enrolment shows similarities, but also differences between men and women. The three most common reasons, career-related reasons, an interest in the topic, and degree-related reasons, are the same. For men, these three reasons account for almost 96% of responses. For women, they account for almost 98%. However, the way male and female learners are distributed over these three reasons is quite different. After combining the results over all courses, women more commonly take part in these four MOOCs because of career-related reasons. Men, on the other hand, take part in these MOOCs about twice as commonly because of a personal interest as women. These differences are notable, since previous research on the association between gender and reasons for enrolment in MOOCs argues that there is little to no association between the reasons for enrolment and gender [66, 26, 28].

A main takeaway from the open-text responses is that MOOCs are not only a low-barrier way to learn about a topic, there are also many learners, both male and female, who are taking part in MOOCs as they want to make a career switch, are taking on new responsibilities, or advancing their current job. By merging closed-response reasons for enrolment across different pre-survey versions, course designers can achieve a more comprehensive understanding of learner motivations over multiple course runs.

This suggests that course content and possibly the marketing strategies should be diversified. To attract more female learners, courses should emphasise career advancement opportunities and professional development. Conversely, to engage male learners, courses should highlight exploratory content. The analysis indicates that the top three reasons for enrolment, namely career, interest, and degree, should guide course design. By integrating practical, career-focused modules with engaging content and highlighting the potential for professional certification, courses could appeal to a broader demographic.

6.2.2. Gender and behavioural engagement

One key observation is the large size of the ‘Sampling’ cluster for both men and women, indicating a common pattern of initial exploration without sustained engagement. This pattern, MOOCs having high dropout rates, are seen often in the literature [4, 87, 91]. This behaviour is more pronounced among women, suggesting that they may be balancing multiple commitments or engaging with MOOCs in a more casual manner. While the flexibility of MOOCs is advantageous in some ways, it may also contribute to superficial engagement if not adequately supported.

Men are also better represented in the ‘Auditing’ cluster than women. This indicates that a larger group of men watch videos throughout the course than women. Within this cluster, we can see that the percentages for women and men fluctuate greatly between courses. We can see that, for UnixTx specifically, far fewer learners fall in the ‘Sampling’ cluster, and instead, many of those learners fall in the ‘Auditing’ cluster.

Women are less likely to fall into the ‘Disengaging’ and ‘Completing’ clusters than men, which are both more engaged than the ‘Sampling’ cluster. This is in line with the literature, which discusses that women drop out more frequently and engage less in online (CS) teaching materials than men [26, 32]. This gender disparity in engagement suggests the need for targeted interventions to maintain and boost engagement among female learners. In addition, providing mentoring opportunities [38], peer interaction platforms [61], and highlighting role models in the field [35, 75] could also help create a more inclusive learning environment.

6.2.3. Gender, reasons for enrolment and behavioural engagement

The study found a significant association between enrolment reasons and engagement patterns for men, but not for women. However, the effect size for both genders was negligible. This aligns with Crues et al. [26], who reported that motivations did not significantly affect persistence. These findings suggest that, while enrolment reasons may play a minor role in engagement, other factors are likely more influential in determining dropout rates. Rizvi et al. [89] argue that certain learning activities can enhance learning for specific socioeconomic backgrounds while hindering it for others. Aldowah et al. [2] identify six key factors that directly impact learner dropout, including academic skills, prior experience, and course design. Onah et al. [81] also highlight that course difficulty and lack of experience significantly affect dropout rates. Itani et al. [58] point out that personal circumstances or a lack of intention to complete the MOOC are also crucial factors.

Furthermore, it was observed that learners who knew the instructor tended to complete MOOCs more frequently than those who enrolled for other reasons. This can likely be attributed to instructors using the MOOC in their actual courses, thereby encouraging completion. Moreover, learners who completed both the pre-survey and engaged with the MOOC were more engaged than those who only participated in the MOOC. This makes sense, as learners are unlikely to complete the pre-survey without intending to engage with the MOOC to some extent.

6.3. Limitations

Like any study, this one also has several limitations that should be acknowledged.

Firstly, there is potential selection bias, as the analysis was conducted exclusively on learners who filled in the pre-survey. These learners may inherently be more engaged, potentially excluding a segment of the population that might demonstrate different levels of engagement and reasons for enrolment.

Additionally, the study was conducted across a limited number of courses, which restricts the generalisability of the findings. The reasons learners have for enrolling and behavioural engagement of learners fluctuate between different MOOCs. Future research should consider a broader range of courses to understand how pervasive these results are.

Another significant limitation is that the closed-ended question changed over the years, currently allowing only four possible answers; the reason is related to the learner's career, interest, studies, or another reason. However, reducing the learner's reasons for enrolment to just one, most important reason, can lose significant information that may be able to guide course designers to fit the course contents better to the learners' needs. Multiple learners who gave an open-text response were classified as 'Other' if they gave a reason that did not fall into a single category.

There is also the issue of face validity, where two questions may not be entirely comparable, potentially impacting the reliability of the responses. Moreover, this study focused exclusively on behavioural engagement, neglecting other dimensions of engagement, such as cognitive, social, and emotional engagement.

There were a few days that did not have log data available, or had corrupted log files. This means that any engagement with the MOOCs was not taken into consideration for these days. Additionally, certain course runs, specifically EX101x-3T2015 (run 2) and EX101x-3T2016 (run 4), include numerous survey responses from learners who did not actually take the course. However, due to the large amount of data, we expect the impact of these effects to be minimal.

Finally, it should be noted that some MOOCs had more participants than others. Therefore, these MOOCs had more effect on the results where the different MOOCs were combined into a single result.

6.4. Future work

There are several avenues for future research that can build on the findings of this study and address its limitations.

Firstly, future studies should consider using more fine-grained timeframes instead of broader assessment periods to measure engagement. This would provide a more detailed understanding of learner engagement patterns over the course duration, enabling course designers to identify critical moments where learners are most at risk of disengaging.

Secondly, it is interesting to explore the underlying reasons why engagement levels differ among learners. Future research should investigate the specific challenges that learners face, as indicated in their responses. Understanding these challenges can help in developing targeted interventions to address and mitigate the factors contributing to disengagement. A more comprehensive engagement model should be employed in future studies. While this study focused on behavioural engagement, incorporating cognitive, social, and emotional dimensions of engagement would provide a more holistic view of learner interactions and experiences within the course.

Improving the automatic classification of reasons for enrolment is another area for future work. The current system, though promising, is too crude for reliable analysis. Enhancing the accuracy and reliability of automatic classification with natural language processing would enable more precise and insightful analysis of open-text responses, leading to a deeper understanding of learner motivations.

Furthermore, the ability to measure behavioural engagement for each course run offers valuable insights into learner dropout points. This facilitates a better understanding of when and what types of interventions are necessary for course instructors. Further research could look into how to raise engagement by data-driven interventions.

Finally, the current survey question in TU Delft MOOCs is one-dimensional, only asking about the learner's primary motivation. However, learners often have multiple reasons for enrolling in MOOCs. A multi-dimensional motivation model, such as the 'Online Learning Enrollment Intentions' scale [66], may lead to a better understanding of the needs of learners.

Addressing these areas in future research will enhance the understanding of online learner behaviour, leading to more effective course design and, hopefully, improved learner outcomes.

6.5. Reflection on research

I want to briefly reflect on my personal experiences doing a larger research project like this. Since this section discusses my personal experiences, I will write it in the 'I' form.

6.5.1. Unsuccessful experiments

I ran multiple unsuccessful experiments throughout this master thesis. Initially, I implemented a k-nearest neighbours approach inspired by Crues et al. [26] for classifying reasons for enrolment. Unfortunately, this did not end up producing meaningfully clustered results, confirmed by applying the elbow method for k-means clustering [27]. The implementation of three models was also planned to model learner engagement in MOOCs: a significant time investment was made into the implementation of 'learning paths' [99], which describe how a group of learners (e.g. male and female learners), navigate through a week using Markov Chains. This implementation was based on one-step chains, describing what percentage of learners in a group go from one element, for example a quiz, to another element, such as the forums. However, as Davis et al. [29] note, "One-step chains can only provide limited insights into more high-level behavioral patterns". The analysis of these one-step chains indeed led to limited insights. Multi-step chains, such as what Davis et al. [29] implemented, could lead to more valuable insights. However, this did not fit the timeframe of this thesis. A cognitive engagement analysis based on video engagement inspired by Sinha et al. [95] was also planned. However, the implementation of the learning trajectories took significantly longer than initially planned due to the differences in courses and course runs, alongside difficulties handling the large amounts of data. Therefore, I chose to focus solely on behavioural engagement.

6.5.2. Learnings

In research, it is not always possible to do everything you want to do. Sometimes, this is due to reasons out of your own control, or simply due to time constraints. Other times, a certain approach does not work. It can be easy to fall victim to the sunk-cost fallacy. At some point, like I had to do multiple times during this project, you have to decide to take a different approach. However, I think this flexibility is important in research. Like any larger project, it is challenging to plan an entire research project from the beginning. I think a research project is more similar to agile software development.

During this project, I learned many things not just about my topic, but also about what research entails. From writing a proposal, discussing ideas with different parties and getting ethical approval, to reading literature, doing experiments and communicating outcomes. I think many of these skills are transferrable to other parts of life.

Throughout my studies, I have gained a variety of skills that have been essential for this thesis. Firstly, I used my database knowledge to create a database, which involved working with an existing system for processing log data and course metadata. Additionally, I applied what I learned in algorithm classes to understand and implement algorithms from research papers into functional code. Given the large amount of log data, I also needed to optimise the code for efficiency. This cost me many hours, but has saved me many more.

Looking back, I realise how much I have learned during my studies. I started university with no programming experience, and now I can build complex software to solve real-world problems. For me, this shows the practical value of my education.

7 Conclusion

The main goal of this research was to gain insights into why men and women choose to enrol in introductory computer science (CS) MOOCs, how they interact with introductory CS MOOCs, and finally, if there was any association between the two. This research was done in the context of introductory CS MOOCs run by the TU Delft between 2015 and 2022. The four selected MOOCs were about data analysis, functional programming, software testing and Unix tools, totalling to thirteen course runs over these four MOOCs. We will now be answering the three research questions posed in section 1.2.

RQ1: What are the differences in reasons for enrolment between men and women in introductory computer science MOOCs?

Across the four different MOOCs, women were more likely to enrol for (prospective) career-related reasons than men, whereas men were more likely to enrol due to an interest in the topic than women. The top three reasons for enrolling — career-related, interest in the topic, and degree-related — were consistent for both women and men. However, the specific reasons for enrolment varied significantly depending on the course topic. Within the open-text responses, there were multiple learners indicating that they were looking to make a career switch, using MOOCs as a low-barrier manner to get into another career field.

RQ2: What are the differences in behavioural engagement between men and women in introductory computer science MOOCs?

Based on the four prototypical trajectories from Kizilcec et al. [65], we found that women fall in the least engaged pattern more commonly than men. Men, on the other hand, are more likely to fall into the other three, higher engagement patterns. A clustering based on these four trajectories gives a high silhouette score, indicating that it makes sense to apply this method to introductory CS MOOCs as well. There is a medium to high association between gender and behavioural engagement. Again, it should be noted that the way learners are distributed over these four clusters varies significantly between different courses.

RQ3: How do reasons for enrolment influence behavioural engagement among men and women in introductory computer science MOOCs?

Combining the results from the previous two research questions, we find that there was a significant association between reasons for enrolment and engagement for men, but not for women. For either group, the effect size of reasons for enrolment is small, indicating that there are likely different factors that can explain the discrepancy in engagement between men and women better than their reason for enrolment can.

We conclude that, while MOOCs offer a promising avenue to increase the participation of women in computer science, simply providing access is not sufficient to ensure high engagement. Women are more likely to enrol in MOOCs for career-related reasons, suggesting that MOOCs could be designed to better support career transitions and professional development for women. However, the lower engagement levels observed among women indicate that additional support mechanisms are necessary.

Course designers should consider implementing more personalized and interactive elements to maintain engagement among female learners. Providing mentorship opportunities, peer interaction platforms, and highlighting role models in the field could also help in creating a more inclusive learning environment. Moreover, further research is needed to identify and address the other factors influencing engagement to ensure that MOOCs can effectively support all learners regardless of gender. By addressing these challenges, MOOCs have the potential to make a significant impact on reducing the gender gap in computer science and empowering more women to pursue and succeed in STEM fields.

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A

Demographics

A.1. Age

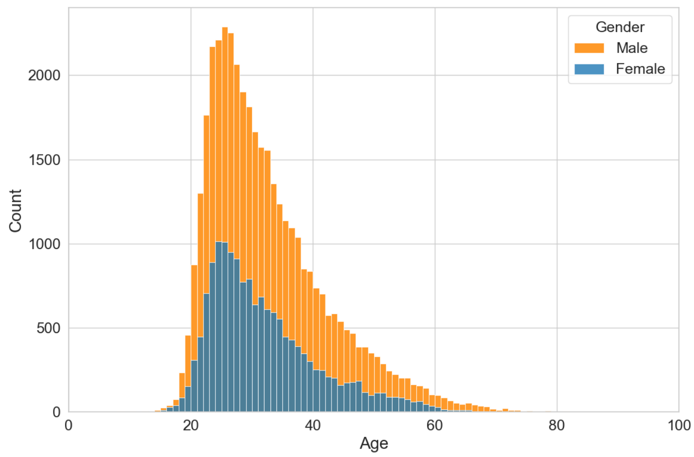

Figure A.1: Age distribution of learners enrolled in EX101x, categorised by gender

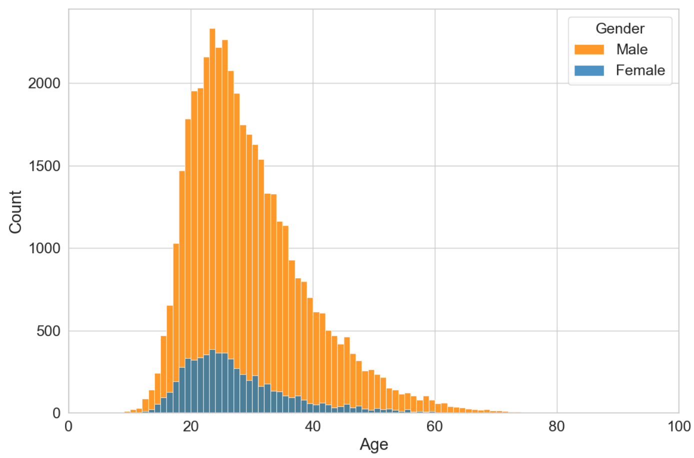

Figure A.2: Age distribution of learners enrolled in FP101x, categorised by gender

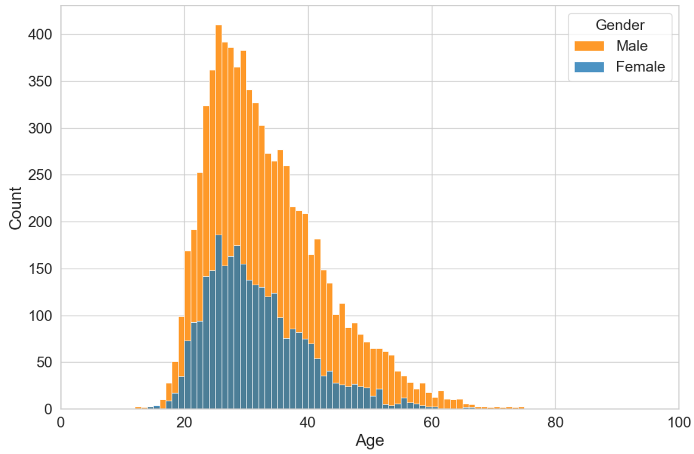

Figure A.3: Age distribution of learners enrolled in ST1x, categorised by gender

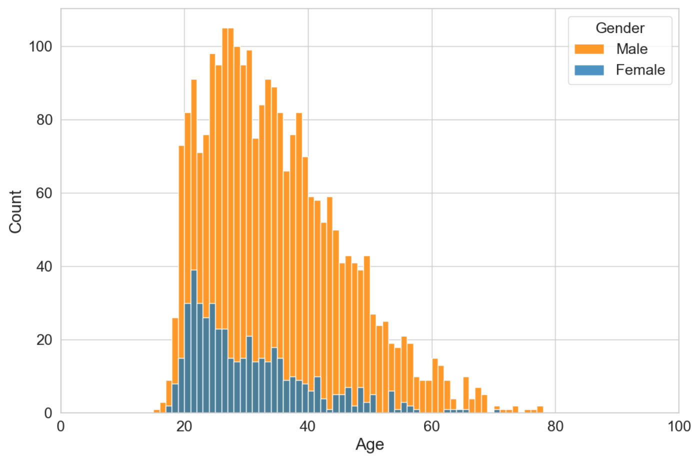

Figure A.4: Age distribution of learners enrolled in UnixTx, categorised by gender

A.2. Location

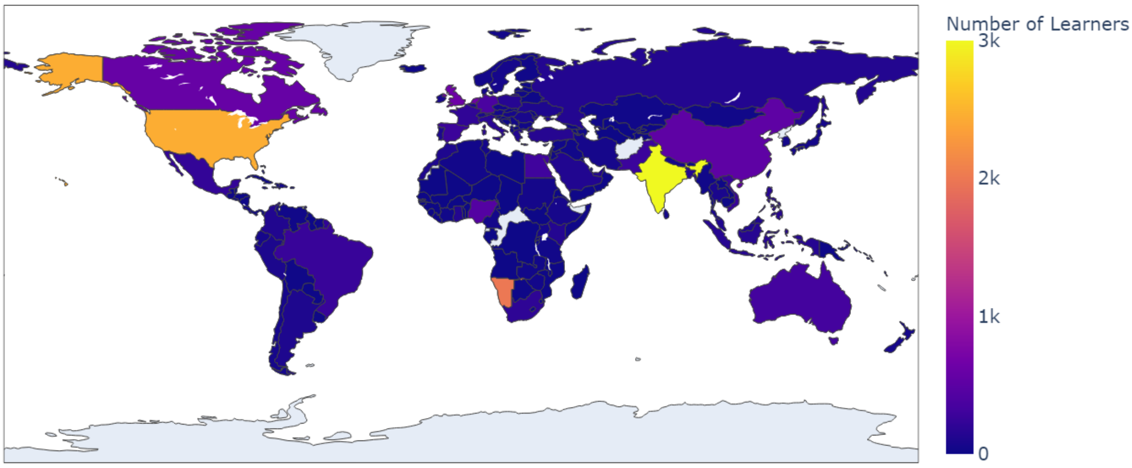

Figure A.5: Map showing the countries of origin for learners enrolled in EX101x, with the number of participants from each country

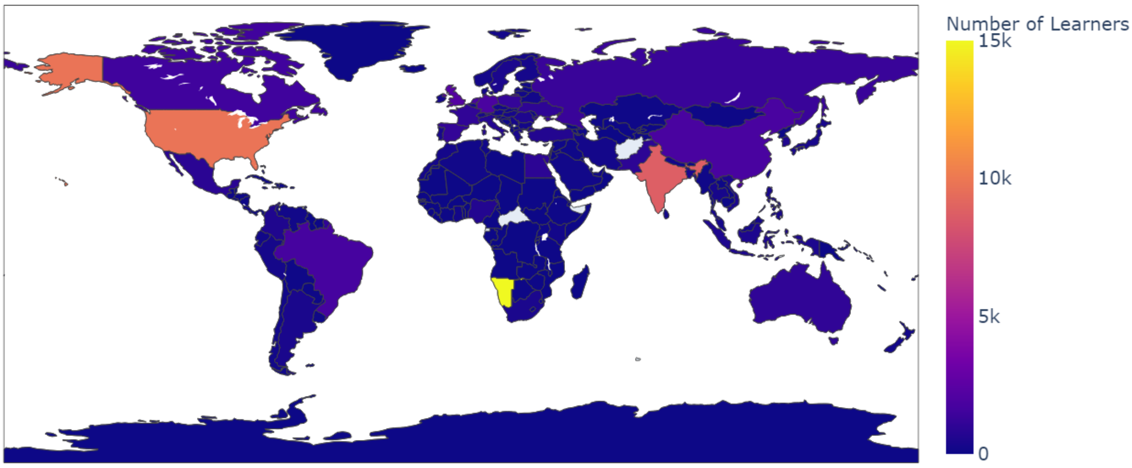

Figure A.6: Map showing the countries of origin for learners enrolled in FP101x, with the number of participants from each country

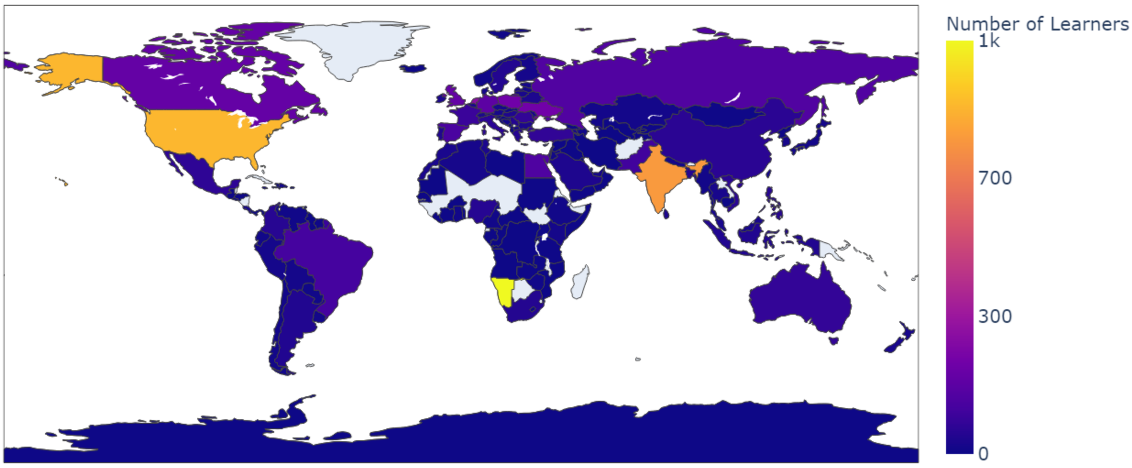

Figure A.7: Map showing the countries of origin for learners enrolled in ST1x, with the number of participants from each country

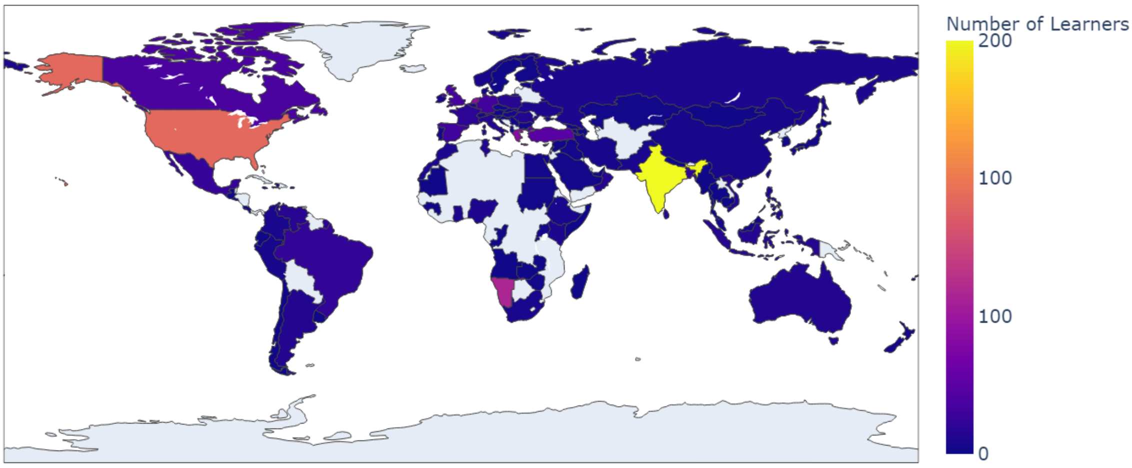

Figure A.8: Map showing the countries of origin for learners enrolled in UnixTx, with the number of participants from each country

A.3. Level of education

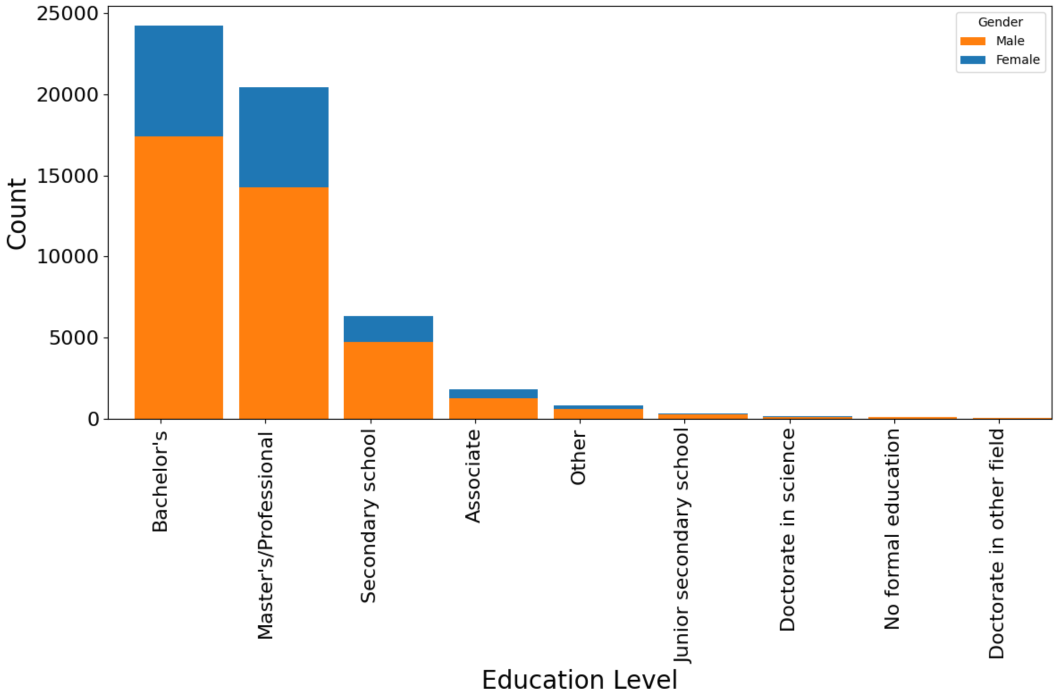

Figure A.9: Education distribution for EX101x

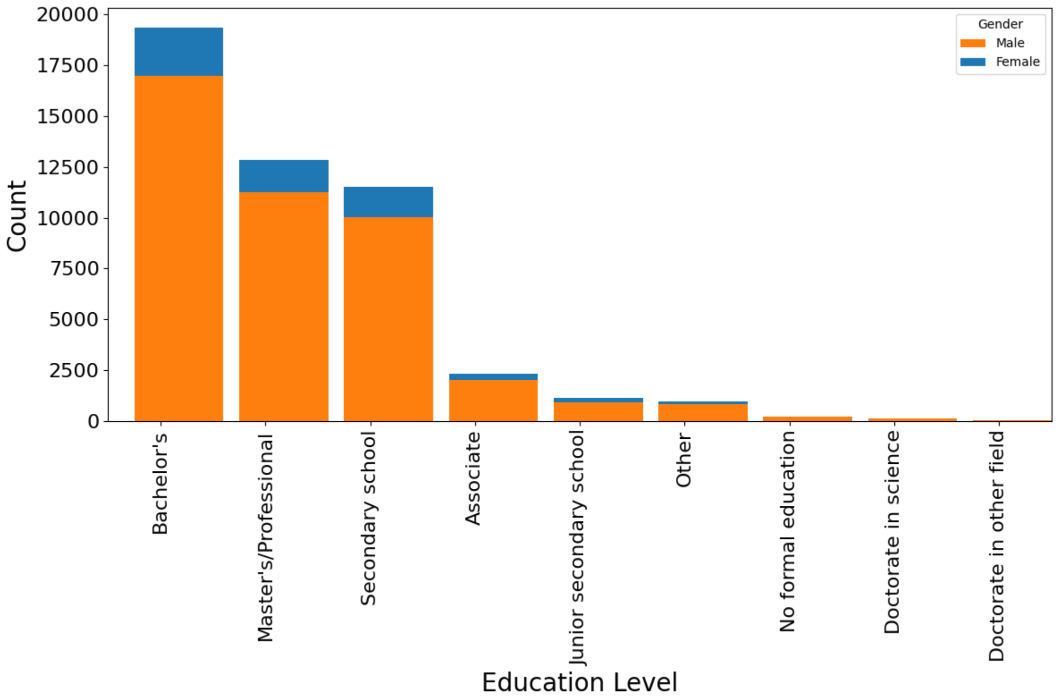

Figure A.10: Education distribution for FP101x

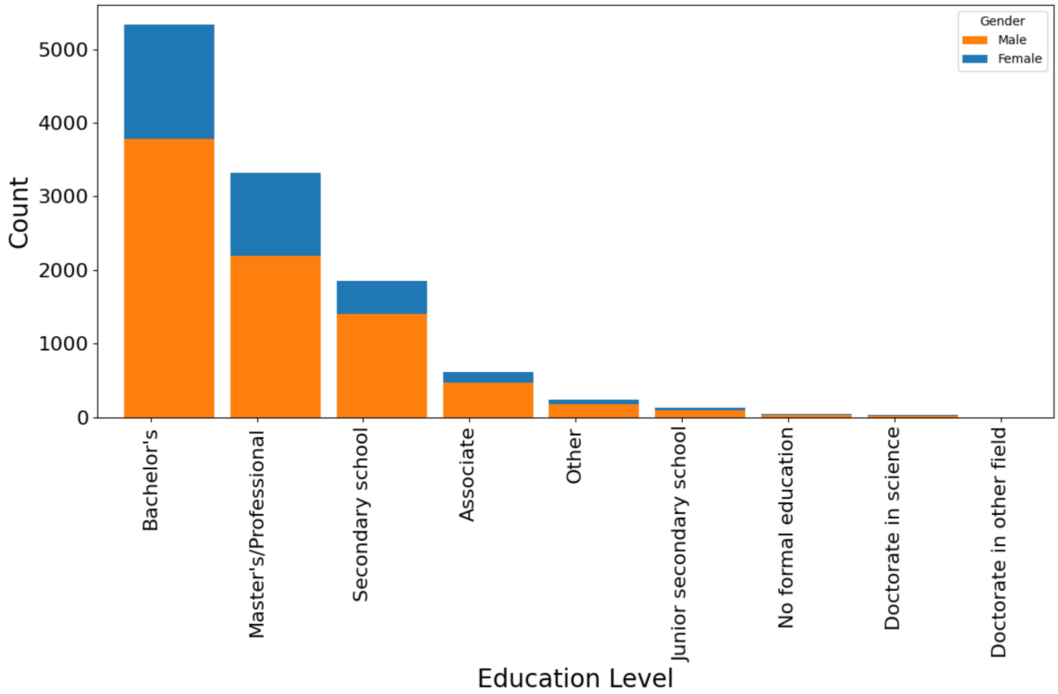

Figure A.11: Education distribution for ST1x

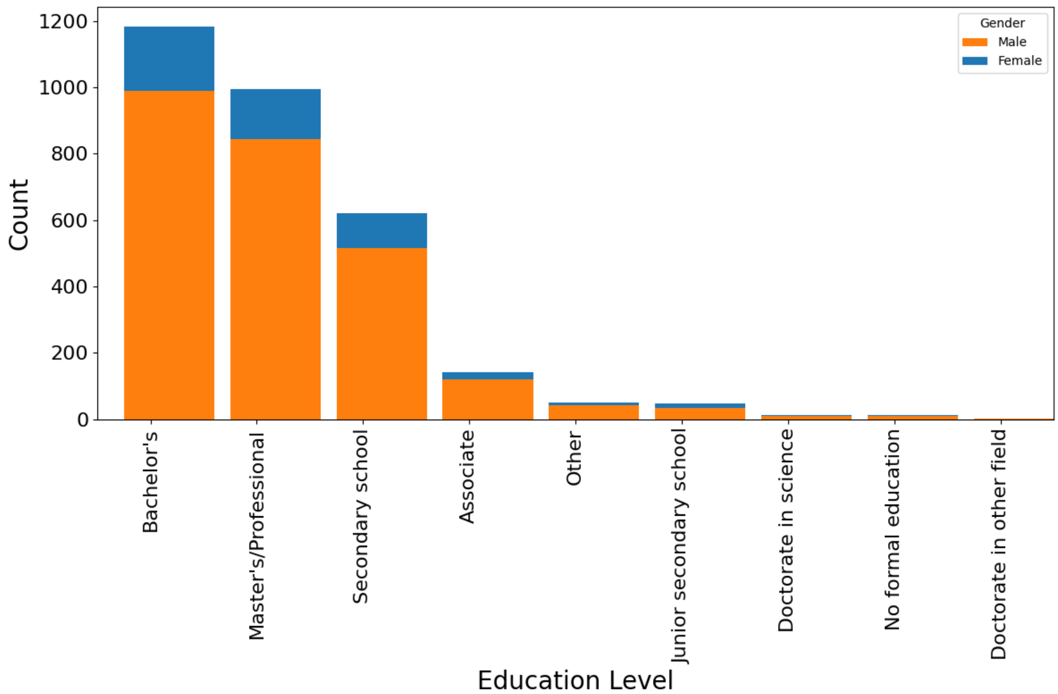

Figure A.12: Education distribution for UnixTx

B

Reasons for enrolment and engagement clusters per course

B.1. EX101x

		Cluster				
		Auditing	Completing	Disengaging	Sampling	Total
Men	Career	310 (12.61%)	429 (17.46%)	521 (21.21%)	1195 (48.72%)	2457
	Degree	7 (5.47%)	21 (16.41%)	28 (21.88%)	72 (56.25%)	128
	Interest	89 (10.96%)	152 (18.72%)	165 (20.32%)	406 (50.00%)	812
	Know the Instructor	1 (10.00%)	1 (10.00%)	3 (30.00%)	5 (50.00%)	10
	Other	9 (26.47%)	7 (20.59%)	3 (8.82%)	15 (44.12%)	34
	Teaching	0 (0.00%)	2 (16.67%)	3 (25.00%)	7 (58.33%)	12
	Total Men	416	612	720	1700	3448
Women	Career	118 (10.09%)	92 (7.87%)	304 (26.01%)	655 (56.03%)	1169
	Degree	2 (4.65%)	3 (6.98%)	10 (23.26%)	28 (65.12%)	43
	Interest	27 (11.30%)	19 (7.95%)	42 (17.57%)	151 (63.18%)	239
	Know the Instructor	0 (0.00%)	1 (33.33%)	0 (0.00%)	2 (66.67%)	3
	Other	2 (10.53%)	1 (5.26%)	5 (26.32%)	12 (63.16%)	19
	Teaching	0 (0.00%)	0 (0.00%)	3 (37.50%)	5 (62.50%)	8
	Total Women	149	116	364	853	1482

Note: Row percentages add up to $\approx 100\%$.

Table B.1: Number and percentage of responses in each of the derived clusters of reasons for enrolling in EX101x, divided by gender.

B.2. FP101x

		Cluster				
		Auditing	Completing	Disengaging	Sampling	Total
Men	Career	140 (18.54%)	152 (20.13%)	222 (29.40%)	241 (31.92%)	755
	Degree	10 (17.24%)	13 (22.41%)	16 (27.59%)	19 (32.76%)	58
	Interest	166 (15.61%)	225 (21.14%)	316 (29.70%)	357 (33.54%)	1064
	Know the Instructor	20 (19.23%)	35 (33.65%)	25 (24.04%)	24 (23.08%)	104
	Other	5 (17.86%)	3 (10.71%)	7 (25.00%)	13 (46.43%)	28
	Total Men	341	428	586	654	2009
Women	Career	4 (7.84%)	5 (9.80%)	15 (29.41%)	27 (52.94%)	51
	Degree	0 (0.00%)	1 (14.29%)	2 (28.57%)	4 (57.14%)	7
	Interest	6 (8.11%)	12 (16.22%)	19 (25.68%)	37 (50.00%)	74
	Know the Instructor	0 (0.00%)	0 (0.00%)	0 (0.00%)	1 (100.00%)	1
	Other	0 (0.00%)	0 (0.00%)	0 (0.00%)	2 (100.00%)	2
	Total Women	10	18	36	71	135

Note: Row percentages add up to $\approx 100\%$.

Table B.2: Number and percentage of responses in each of the derived clusters of reasons for enrolling in FP101x, divided by gender.

B.3. ST1x

		Cluster				
		Auditing	Completing	Disengaging	Sampling	Total
Men	Career	129 (25.60%)	69 (13.69%)	146 (28.97%)	188 (31.75%)	504
	Degree	14 (21.88%)	7 (10.94%)	18 (28.13%)	21 (32.81%)	64
	Interest	13 (15.12%)	6 (6.98%)	27 (31.40%)	29 (46.51%)	86
	Other	0 (0.00%)	0 (0.00%)	1 (50.00%)	1 (50.00%)	4
	Teaching	4 (30.77%)	0 (0.00%)	6 (46.15%)	3 (23.08%)	13
	Total Men	160	82	198	242	682
Women	Career	63 (24.61%)	20 (7.81%)	63 (24.61%)	110 (42.97%)	256
	Degree	10 (38.46%)	6 (23.08%)	8 (30.77%)	9 (34.62%)	26
	Interest	5 (21.74%)	2 (8.70%)	8 (34.78%)	10 (43.48%)	23
	Other	1 (50.00%)	0 (0.00%)	1 (50.00%)	1 (50.00%)	3
	Teaching	0 (0.00%)	0 (0.00%)	1 (25.00%)	3 (75.00%)	4
	Total Women	79	28	81	133	321

Note: Row percentages add up to $\approx 100\%$.

Table B.3: Number and percentage of responses in each of the derived clusters of reasons for enrolling in ST1x, divided by gender.

B.4. UnixTx

		Cluster				
		Auditing	Completing	Disengaging	Sampling	Total
Men	Career	30 (18.29%)	19 (11.59%)	57 (34.76%)	58 (35.37%)	164
	Degree	10 (20.41%)	3 (6.12%)	22 (44.90%)	14 (28.57%)	49
	Interest	11 (19.30%)	3 (5.26%)	24 (42.11%)	19 (33.33%)	57
	Other	1 (25.00%)	0 (0.00%)	1 (25.00%)	2 (50.00%)	4
	Total Men	52	25	104	93	274
Women	Career	8 (15.69%)	2 (3.92%)	15 (29.41%)	26 (50.98%)	51
	Degree	0 (0.00%)	1 (8.33%)	6 (50.00%)	5 (41.67%)	12
	Interest	0 (0.00%)	1 (16.67%)	5 (83.33%)	0 (0.00%)	6
	Other	0 (0.00%)	0 (0.00%)	0 (0.00%)	1 (100.00%)	1
	Teaching	2 (100.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	2
	Total Women	10	4	26	32	72

Note: Row percentages add up to $\approx 100\%$.

Table B.4: Number and percentage of responses in each of the derived clusters of reasons for enrolling in UnixTx, divided by gender.