

Enrollment Motivations in an Online Graduate CS Program: Trends & Gender- and Age-Based Differences

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ABSTRACT

Demand for CS education has risen, leading to numerous new programs, such as the rise of affordable online degrees. Research shows these programs meet an otherwise untapped audience of working professionals seeking graduate-level CS education. In this study, we examine the motivations for enrollment among students in one such online MSCS program. Based responses to an open-ended question, we develop a typology of motivations, including goals (e.g. career transition), opportunities (e.g. enrolling without taking time off work), and assurances that their goals will be met (e.g. the program's accreditation). We then issue a closed survey question to a new group of students to further explore these motivations. In this paper, we discuss both aggregate and demographic trends in motivations, including the different motivations of men and women and what they imply about the program's impact on the gender divide in computing. We also examine older students' tendency towards intrinsic motivation to pursue an MSCS degree.

CCS CONCEPTS

• Social and professional topics~Computing education • Social and professional topics~Adult education

KEYWORDS

Online education, graduate CS education, adult learners.

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1 Introduction

Demand for computer science education has been rising over the past decade [32][33]. This has had a significant impact on undergraduate enrollments [30], but has also led to an expansion in other types of offerings, including MOOCs (massive open online courses) [20], coding boot camps [2], and online graduate degrees. Among online graduate degrees, a rising trend has been affordable degrees at scale or “Limeades” (Large, Internet-Mediated Asynchronous Degrees), programs offered online at a steep discount relative to their on-campus counterparts, often in partnership with MOOC platforms [23]. As of August 2019, the three largest MOOC partners engaging in university partnerships (Coursera, edX, and FutureLearn) together advertise 57 online degrees; four of these are in computer science, and an additional 15 are in computing-related fields like analytics, cybersecurity, and information technology.

Analyses of one early entrant into this space have found several differences between the online student body and its on-campus counterpart. Entrants into the online program were found to be unlikely to have enrolled on-campus elsewhere if the online option were not available, thus expanding access to a previously underserved group [17]. Online students were older and more likely to be American, mid-career, and juggling family and work obligations [18]. Enrollment in the online program did not diminish applications to the school's on-campus program; in fact, they rose after the launch of the online program [24].

These findings, as well as the overall growth of the program (enrolling 8,700 students in Spring 2019), indicate a significant interest in flexible, affordable graduate-level CS education. The question remains: why are they demanding this education? One might hypothesize that the motivations are largely extrinsic (higher pay, career advancement), but a prior study found that online students have more intrinsic and altruistic motivations when seeking positions as teaching assistants than on-campus students [22]; do those alternative motivations extend to their reasons for enrolling in the first place? In this study, we ask the question: why do these learners say they enroll in these programs? We discover that the answer to this question is multifaceted: there are, as we would expect, goals they want to achieve, but we find two other frequently-reported categories of reasons: assurances that their goals will be met, and opportunities to meet those goals they were lacking otherwise.

2 Related Work

This work sits at the intersection of several well-developed fields: adult education, distance learning, online education, lifelong learning, and motivation. The straightforward context behind this work is that while adult education has been researched for decades (e.g. [26]), rapid technological changes spurred an increased demand for lifelong learning around the turn of the last century [12][13][14]. Technology soon filled in those gaps [15], ultimately leading to initiatives like MOOCs to meet this demand [25][35].

More specifically, this research investigates the motives behind adult learners' choice to pursue continued education in the first place. Research in this area has focused on identifying the demographic, personality, and professional profile of adult learners who pursue continued education [1][21][29] or on how to motivate adult learners who are already participating [31][34][38]. Some work has explored the motivations of these learners; for example, Coker [5] examines the motivations of African-American women in pursuing adult education, finding more intrinsic desires.

This work also touches on age- and gender-based differences in interest in careers in computing, separate from the role of adult education. The digital divide in computing is well-documented with respect to both gender [4][7] and race [36]. Several explanations have been posed to this gender gap with varying degrees of evidence, indicating that there is no single or small set of reasons to explain this gap [4][8][37]. In this work, we turn to a different way of investigating this question: to understand whether women who do seek CS education are motivated by different factors than men. Understanding these motivations could lead to new initiatives to emphasize meeting women's differential needs and goals.

3 Study Context

There are two important contexts for this study. First, there is the context of the program as a whole in which we are investigating these students. Second, there is the specific context of the data that was gathered.

3.1 Program Context

The program under investigation in this study is an online Master of Science in Computer Science program offered by a major public research institution in the United States. The program launched in 2014, and by the Fall 2019 semester enrolled 9,000 total students. Prior work has identified three significant distinguishing features of the program: its cost, its accreditation, and its flexibility. The program is priced at ~\$8,000 in total tuition for the entire degree and is considered to be an alternative campus for the same degree, giving it the benefit of the same accreditation with no distinction in the final diploma that is issued. The program is designed for geographic and temporal flexibility: students never visit campus or testing centers, nor are required to tele-attend synchronous lectures.

Prior research has revealed significant differences between the demographics of this program and its on-campus analogue. Students tend to be older and are more likely to permanently reside in America and have full-time employment [18]. Research has also found that the online program draws more underrepresented minorities and fewer women; the latter trend has been diminishing as the program has matured and may be due to the interaction between gender and nationality: a greater percentage of international students both online and on-campus are women, and the on-campus program draws more international students overall [24].

3.2 Data Context

In the first phase of the study, students in four classes were asked at the start of the Spring 2019 semester to answer the question in plaintext, "Why did you enroll in the program?" This question was asked as part of a start-of-course survey for which students earned a small amount of class credit (less than 1% of their course grade). The decision to recruit respondents from enrollees in current classes was deliberate: one goal was to monitor whether duration in the program affected how students replied to the question. 1,850 students responded to this survey; 98 of these responses were excluded from analysis as the students responded in multiple classes. Response rates for the four classes were 80%, 81%, 73%, and 81%.

In the second phase of the study in Fall 2019, we revised this question to ask students to select from a list of potential motivations based on our analysis of answers to the previous semester's question. This question was offered to students in the same four classes in this new semester.

4 Methodology

We used a grounded coding approach to develop our coding scheme, and then a team of three raters (who we refer to as Rater 1, Rater 2, and Rater 3) coded the survey responses. The coding scheme was then used to develop prescribed responses for a subsequent survey. The results from coding the free response survey and from administering the prescribed response survey were then analyzed to determine trends in the data.

4.1 Developing the Coding Scheme

The free response survey was administered across four classes in the Spring 2019 semester. The results from this survey were combined into a single list of responses. Duplicate responses (any students who responded in more than one class) were removed, yielding 1,752 remaining responses. These responses were then randomized.

Rater 1 then coded the first 100 responses using a grounded coding approach. Responses were coded at the response level, although each response could have multiple codes assigned to it. Allowing for multiple codes per response was necessary because nearly all respondents gave more than one reason for enrolling in the program. From this grounded coding, we identified 14 distinct reasons.

Table 1: Codes developed through this coding process.

Code	Definition	Example
Goals		
Knowledge	The student wants to obtain the type of knowledge the program imparts.	“Broaden the scope of my CS knowledge.”
Degree	The student wants to obtain a Master’s degree.	“I want to get a Masters Degree in Computer Science from a top quality school.”
Advancement	The student wants to preserve their competitiveness and/or advance in their career.	“I am seeking a master’s degree in computer science in order to put myself in a competitive professional position.”
Transition	The student wants to transition to a new career.	“I am hoping to leverage this degree to change careers into software development or data science. “
Pleasure	The student wants to participate for their own enjoyment.	“I’m a lifelong learner and I enrolled to get access to some interesting classes.”
Compensation	The student wants to obtain a higher salary.	“Wanna get a Master’s degree since I believe I’ll get some salary increase.”
Research	The student wants to pursue a PhD or other future research endeavors.	“I want to earn a doctorate; teach and continue research in the field of machine learning.”
Contribution	The student wants to contribute to the field itself.	“I’m interested in using [AI] to improve lives everywhere and try to solve complex issues.”
Community	The student wants to connect with a community with similar interests.	“I believe that formalized learning through structure and with a cohort of learners is the best way.”
Opportunities		
Cost	The student could enroll due to the low tuition price.	“[The program]’s cost is just unbelievable! Especially for the quality offered!”
Flexibility	The student could enroll due to the geographic or scheduling flexibility of the program.	“My family relies on me for an income and it is not feasible for me to quit my job to pursue a post-graduate degree.”
Assurances		
Prestige	The student respected the credibility of the granting institution.	“I was always dreaming about by obtaining a degree from a renowned US tech university.”
Rigor	The student respected the expected rigor of the program’s curriculum.	“The degree’s reputation is a major reason why. I feel like, based on what I’ve heard, it’s a challenge worth the (likely large) time investment.”
Faculty	The student respected the faculty associated with the program.	“Getting to learn from renowned faculty in the field of AI/ML.”

In addition to these 14 distinct codes, the raters devised a hierarchy to help structure the results. This hierarchy does not factor into the actual coding or analysis; it is solely used to think about the results. The 14 codes were divided into three higher-order categories: Goals, which are what the respondent wanted to accomplish or attain; Opportunities, which are the absence of obstacles previously preventing them from attaining those goals; and Assurances, which are affirmations that they would accomplish those goals. Table 1 provides names, definitions, and examples for all 14 codes, divided by these three categories.

Next, each rater coded the same batch of 50 responses to check for inter-rater reliability and to determine if the codes were comprehensive and distinct. The codes were determined to be appropriate, and no new codes were discovered. The Kappa statistic was calculated between each pair of raters and found to be: 0.791 between Rater 1 and Rater 2; 0.787 between Rater 1 and Rater 3; and 0.795 between Rater 2 and Rater 3, indicating “substantial agreement” [28], giving us confidence that we could maintain reliability with one rater coding each of three batches.

4.2 Coding the Responses

The remaining 1,602 responses were split into three batches, each coded by a single rater. Blank responses and responses where the respondent abstained noting they answered the question in a previous semester were coded as “Blank”. A small number of responses indicated uncertainty about why the respondent enrolled in the program or used unclear wording; these responses were coded as “Unsure/Unclear”.

During this process, all three raters identified two potential codes that were absent from the initial set on which the scheme was developed: Structure, an Assurance code, which is the desire to have an external structure placed on their own education to improve their outcomes or likelihood to succeed (e.g. “Doing a

structured course ensures that I am dedicatedly learning instead of one-off boosts in a self-learning environment”, as one respondent said); and Content, a Goal code, which is the desire to learn very specific types of content available in the program (e.g. “I would like to get more knowledge on Artificial Intelligence and Machine Learning”, as one respondent said). Because these were not identified in the initial set, they were not rigorously tracked when coding the entire data set, but they were included during the next phase.

4.3 Developing the New Survey

In Fall 2019, the start-of-course survey administered to the four classes was updated to allow students to select multiple prescribed possible reasons for enrolling options from a list: the list of codes developed from the grounded coding, plus the two additional options identified while coding the full set. An “Other” option was included for students who had a reason for enrolling that was not on the prescribed list. Responses to this survey were collected and analyzed to examine how student response patterns might change when primed on possible reasons rather than asked to generate their reasons themselves.

5 Analysis

After omitting the responses used to generate the coding scheme and those responses coded simply as “Blank” or “Unsure/Unclear”, we analyzed the remaining responses and codes. This final data set comprised 1,368 responses, with a total of 2,457 codes applied to them. We also analyzed the 1,762 prescribed response surveys, which had a total of 12,807 student-selected prescribed reasons for enrolling in the program. Students were also asked a handful of demographic questions, allowing us to subdivide responses based on four demographic categories: age, gender, prior education, and classes completed so far. Respondent who skipped the demographic questions were excluded from the segmented analysis. The most interesting trends we observed related to age and gender; trends regarding prior attainment and progress through the program, while present, are out of scope for this analysis.

5.1 Overall Trends

We first look at any trends that appeared in our aggregate analyses of both the free and prescribed response surveys.

5.1.1 Free Response Survey. A summary of the overall trends for the free response survey can be found in Figure 1. There are a number of interesting trends present in this summary. First, we note that we might infer a sub-level inside the overall category of Goals: some goals are extrinsic – tied to an external, objective value (Advancement, Transition, Degree, Compensation) – while others are more intrinsic to the individual (Knowledge, Pleasure, Community, Contribution, Research). We note that those codes that we might consider extrinsic comprise 34.02% of codes assigned, while those codes we might consider intrinsic comprise 38.59%, a statistically significant difference at $\alpha = 0.05$ ($X^2 = 6.175$, $p = 0.0130$). This suggests, in line with prior research [22], that students in this online program may be as or more intrinsically motivated rather than extrinsically. We find this hypothesis compelling given the low cost of the program; at only \$7,000 rather than several times more, it is reasonable for students to pursue the program as a personal passion rather than as an investment.

Second, we find it noteworthy that Flexibility appears more often (7.85% of assigned codes) than Cost (4.32%) with statistical significance ($X^2 = 14.9$, $p < 0.0001$). Much of the press for the program has been derived from its low cost, yet students appear to suggest that it is actually the program’s distributed asynchronicity that is of higher value. We similarly find this hypothesis compelling given the program’s large audience of mid-career professionals; the opportunity cost of years out of the workplace and the personal cost of moving a family may be larger deterrents than tuition. Mid-career professionals may be more likely to have employer tuition assistance and similar benefits, making them less sensitive to tuition. The two codes are also heavily coincident: 74 respondents were coded as citing both Cost and Flexibility, compared to only 42 for Cost (without Flexibility) and 137 for Flexibility (without Cost).

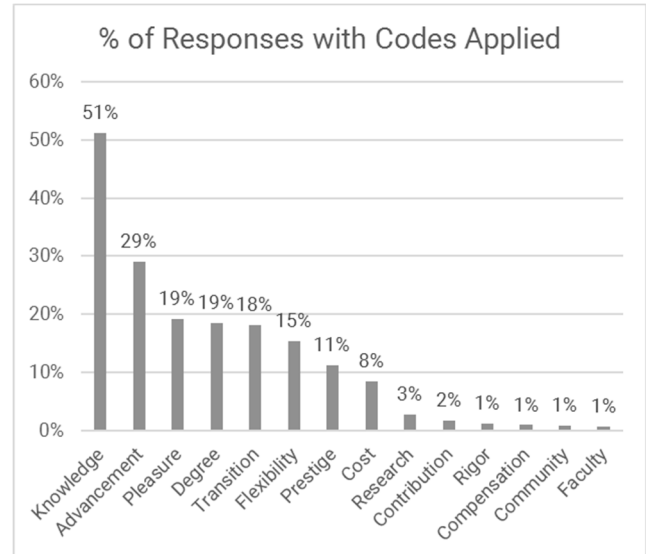


Figure 1: The fraction of responses to the free response survey question including each type of motivation.

In both these cases, however, we suspect biases may be introduced based on perception of the question; for instance, we do not believe that only 4.32% of respondents care about the low cost, but rather that many students do not perceive cost as a reason “why” they enrolled. The prescribed response survey was developed in part to explore this possible definitional difference.

5.1.2 Prescribed Response Survey. As noted in the Methodology section, after establishing the coding scheme based on free responses, we then offered students in a subsequent semester the 16 identified codes. This analysis examines the extent to which the raw and relative frequency of these reported motivations changes when they are offered to students as options, but also to assess whether new trends emerge. Figure 2 shows the relative frequency of each response, as well as the overall segment of reported motivations each code represents.

A number of notable differences stand out. First and most obviously, students report significantly more motivations when offered these options than when asked to generate their motivations themselves. While each response in the prior analysis was assigned an average of two motivations, students selected an average of 7.27 motivations when offered a list. This may be due to a priming effect, where students retrospectively select a motivation they did not actually hold based on seeing it offered; it may be due to a recognition vs. recall effect, where students recognize having held a motivation that they forgot when asked merely to recall their motivations; and it may be due to the interpretation of the question, where students previously did not report motivations like Cost and Flexibility because they did not consider them topical to the question. In any case, one effect of this altered dynamic is it reframes the question from listing the most important motivations to selecting all present motivations, regardless of importance.

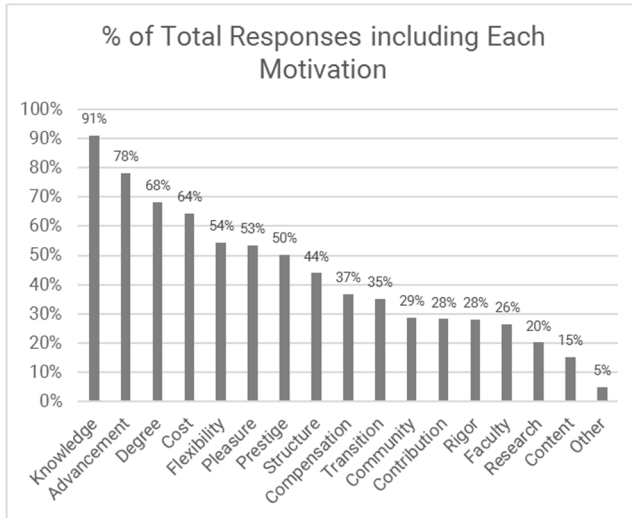


Figure 2: The fraction of responses to the free response survey question including each type of motivation.

Second and relatedly, the greatest difference between the free-response answers and the prescribed response answers is the dramatic rise in students noting Opportunities (Cost and Flexibility) and Assurances (Prestige, Rigor, and Faculty) as motivations. While Cost and Flexibility appeared in only 8.48% and 15.42% of free-response answers and rank as the 9th and 7th most common motivations, they appear in 64.30% and 54.48% of prescribed response answers and rank as the 4th and 5th most common motivations (all figures reflect Cost and Flexibility respectively). The prestige of the school, cited in only 11.26% of free responses, was selected by over half of respondents. The program’s rigor and the quality of the faculty rose from 1.17% and 0.66% to 28.04% and 26.33% respectively.

Third, while most motivations stayed close to the same spot relative to others, a handful plummeted in frequency: career transition, the 5th most common at 15.54% of free responses, dropped to 10th most common at 35.13% of prescribed responses. Research goals, 10th at 2.78% of free responses, dropped to 15th at 20.20% of prescribed responses. The drop in relative frequency suggests students these motivations were more likely to be reported if present, while other motivations were more likely to go unreported even if they were present. This may be due to their lack of relative universality: anyone in the program will receive knowledge and a degree, whereas not everyone completing the program will attain a career transition.

Fourth, the previously-observed difference between intrinsic and extrinsic goals disappears: 30.45% of reported motivations are intrinsic goals, while 30.01% are intrinsic goals. Within Goals, the only major change is the rise in Compensation as a motivation, from present in 0.95% of free responses to present in 36.72% of prescribed responses, moving it past career transition.

Although the trends across the two surveys are similar, there are notable interesting differences, such as the relative value of

Cost vs. Flexibility and intrinsic vs. extrinsic goals; a question may be asked which of these sets of answers more accurately portrays students’ motivations. We argue that neither is more accurate than the other; rather, they answer related but subtly different questions. When asked to generate their motivations, students more readily emphasize intrinsic motivations, although when prompted they select extrinsic motivations with equal frequency. While Cost is a factor to a larger number of students, Flexibility appears to be more important to those students who require it at all. While few students cite their faith in the program among their motivations, assurances that it is valuable like the school’s Prestige are selected by over half of students, reflecting its more implicit importance.

5.2 Gender Trends

We next look at the notable gender differences that existed on the free response and prescribed response surveys.

5.2.1 Free Response Survey. Generally, most gender differences are small: no statistically significant differences were observed in each gender’s likelihood to report knowledge, career advancement, personal interest, degree attainment, or career transition. Two statistically significant differences were observed among the less-reported motivations, however; women were more likely (18.82%) to report flexibility as a motivation than men (14.51%) ($X^2 = 5.232, p < 0.05$), while men were more likely (11.79%) to report school prestige as a motivation than women (8.24%) ($X^2 = 4.646, p < 0.05$). Hypotheses for the former difference include that women may perceive themselves as at greater risk of losing what professional progress they have attained by leaving work to seek more education, or that women in the program may be more likely to be fulfilling caretaker roles at home and thus derive additional benefit from its flexibility.

5.2.2 Prescribed Response Survey. Women again selected flexibility and career transition more often than men, and in fact, the gap in reporting grew from 3.02% to 7.28% for flexibility and from 2.37% to 7.14% for career transition. However, these two reasons no longer accounted for largest disparities. Larger differences were found within the areas of personal interest (reported by 14.51% fewer women, 56.67% to 41.26%) and salary increase (reported by 14.11% fewer women, 39.61% to 25.50%). These disparities may be a consequence of the gender gap in computing fields. The motivations reported more often by men imply a desire to augment existing computing careers, whereas those favored by women imply a desire to enter the field. This suggests (although further research is needed) that affordable online programs like this one, despite demonstrating a gender gap similar to traditional programs, may nonetheless address the gender divide in computing by specifically appealing to women who are not already in the industry, but men who already are.

5.3 Age Trends

Finally, we look at differences among respondents from different age groups for each survey. Respondents self-selected into age groups: <18; 18-24; 25-34; 35-44; 45-54; 55-64; and 65+.

5.3.1 Free Response Survey. Regarding student age, we observed three notable trends. First, the likelihood that a student mentions knowledge acquisition as a motive dropped steadily as age rose, from 60.11% of students ages 18-24, to 52.18% of those 25-34, down to 42.11% of those 55-64. Second, the likelihood that a student mentions personal interest rose as age increased, from 15.17% for students aged 18 to 24 to 24.32% for ages 45 to 54. Third, the likelihood that a student mentions flexibility dropped as age rose, from 20.22% for those 18-24 down to 5.26% for those 55-64, with a steady drop in between.

Put together, we suspect that this indicates that the younger students are more likely to be motivated by the realization that they have some specific gaps in their knowledge coming out of their undergraduate degrees that they need to address, while older students are more likely to think of the ongoing learning as worthwhile because it is broadly interesting or fun to pursue. Regarding flexibility, we hypothesized that this response would be more heavily favored by mid-career professionals who would be more likely to be constrained by family obligations and major investments like homes, but it appears that the ability to pursue further education while working may be valued even more highly by young students with student loans.

5.3.2 Prescribed Response Survey. Among ages 55-64, there was a large increase in reporting Community (from 0% to 56.25%) and Faculty (0% to 62.50%) as reasons for enrollment across the two surveys, and this age group reported these reasons significantly more frequently than the other age groups on the prescribed response survey. Additionally, within this age group, these two reasons were cited more often than career transition, which was originally the 3rd-most common response on the free response survey. Older students who have likely been working longer than other students may instinctively value the practical, achievement-related implications of completing the program and acquiring a master's degree, and they may not have considered other reasons for enrolling until prompted with them.

6 Discussion

The prior analyses delved into highly specific distinctions; in this discussion, our goal is to step back and identify some notable overall trends in the types of students who seek these new affordable online degrees. Toward this end, we reiterate that we consider the two surveys—free and prescribed response—to be different probes into the underlying motivations of these students. We hypothesize that free responses better capture what students find most important, while prescribed responses control for differing interpretations of the question.

Abstracting away from the details, we find four notable trends. The first is derived from the overall trends present in the responses. Due to a lack of data regarding on-campus programs, we cannot compare this audience with that of traditional graduate programs; given their high cost of tuition, though, we find it a reasonable hypothesis that the majority of students seeking traditional programs expect a significant return on investment. In our surveys, we find that online students are

equally or more motivated by intrinsic gains (knowledge acquisition, personal interest, community engagement, or research pursuits) as by extrinsic returns (career advancement or transition, degree attainment, salary increases). This aligns with prior research finding a higher rate of intrinsic and altruistic motivations among online teaching assistants [22], and with research finding the audience for this degree program would not otherwise have enrolled in traditional graduate education [17].

Second, we note the significant differences in motivations to enter the program based on gender. Women were more likely to cite career transition and the program's flexibility as significant factors. Men, on the other hand, were more likely to select personal interest and salary increases. This suggests women are more likely to use the program as a route into the tech industry, whereas men are more likely to use it to solidify their existing role. This further suggests that the flexibility of online education may be an avenue to address the gender divide in computing.

Moreover with regard to gender, we also note the absence of certain differences we had hypothesized. One aspect of imposter syndrome is a reluctance to make mistakes that would confirm to the world that one is an imposter [6], and given the skepticism surrounding online education [16], we suspected that a significant factor for women experiencing imposter syndrome with regard to computing [11] may be assurances as to the program's rigor, prestige, and faculty quality. However, no gender-based differences were observed for these reasons.

Third, older students were observed more likely to report intrinsic motivations behind enrollment in the program. This holds true across multiple motivations: although all age groups report knowledge acquisition as a significant motivator, the prevalence of personal interest rises with age. Motivations like degree attainment, salary increases, and career advancement drop as age rises. This is notable when considered in conjunction with the program's demographics; it may be that case that the online program attracts more intrinsically-motivated learners; it may attract older learners who in turn are more intrinsically-motivated; or it may attract intrinsically-motivated learners who in turn are likely to be older. This has significant implications as to whether these programs are directly appealing to the needs of working professionals, or whether they are appealing to a set of criteria independently common among working professionals.

Finally, for those reporting Career Transition as a motivation, it is tempting to assume these students would be non-technical individuals seeking lucrative computing careers. A notable minority was found, however, of students already in computing careers expressing a desire to switch into teaching roles, many of which required a Master's. A similar audience was observed of current teachers wishing to be eligible to teach computer science in addition to their existing teaching responsibilities. Thus, the program may solve an additional problem of expanding the pipeline of computing teachers; it provides an avenue for working professionals to transition to careers as CS teachers and for current teachers to add CS to their repertoires without incurring significant additional opportunity costs.

REFERENCES

- [1] Belanger, P., & Valdivielso, S. (1997). *The Emergence of Learning Societies: Who Participates in Adult Learning?* Elsevier Science Inc..
- [2] Burke, Q., Bailey, C., Lyon, L. A., & Green, E. (2018, February). Understanding the Software Development Industry's Perspective on Coding Boot Camps versus Traditional 4-year Colleges. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education* (pp. 503-508). ACM.
- [3] Caffarella, R., & Merriam, S. B. (2000). Linking the individual learner to the context of adult learning. *Handbook of Adult and Continuing Education*, 55-70.
- [4] Chang, E. (2019). *Brotopia: Breaking Up the Boys' Club of Silicon Valley*. Portfolio.
- [5] Coker, A. D. (2003). African American female adult learners: Motivations, challenges, and coping strategies. *Journal of Black Studies*, 33(5), 654-674.
- [6] Clance, P. R., & Imes, S. A. (1978). The imposter phenomenon in high achieving women: Dynamics and therapeutic intervention. *Psychotherapy: Theory, Research & Practice*, 15(3), 241.
- [7] Cooper, J., & Weaver, K. D. (2003). *Gender and computers: Understanding the digital divide*. Psychology Press.
- [8] Croasdel, D., McLeod, A., & Simkin, M. G. (2011). Why don't more women major in information systems?. *Information Technology & People*, 24(2), 158-183.
- [9] Cross, K. P. (1981). *Adults as Learners: Increasing Participation and Facilitating Learning*. Jossey-Bass.
- [10] Falasca, M. (2011). Barriers to adult learning: Bridging the gap. *Australian Journal of Adult Learning*, 51(3), 583-590.
- [11] Falkner, K., Szabo, C., Michell, D., Szorenyi, A., & Thyer, S. (2015, June). Gender gap in academia: perceptions of female computer science academics. In *Proceedings of the 2015 ACM Conference on Innovation and Technology in Computer Science Education* (pp. 111-116). ACM.
- [12] Field, J. (2000). *Lifelong learning and the new educational order*. Trentham Books, Ltd..
- [13] Fischer, G. (1999, April). Lifelong learning: Changing mindsets. In *Proceedings of the ICCE 1999 Conference* (pp. 21-30). Omaha: IOS Press.
- [14] Fischer, G. (2000). Lifelong learning—more than training. *Journal of Interactive Learning Research*, 11(3), 265-294.
- [15] Fischer, G. (2001). Lifelong learning and its support with new media. *International encyclopedia of social and behavioral sciences*, 13, 8836-8840.
- [16] Fogle, C. D., & Elliott, D. (2013). The market value of online degrees as a credible credential. *Global Education Journal*, 3.
- [17] Goodman, J., Melkers, J., & Pallais, A. (2019). Can online delivery increase access to education?. *Journal of Labor Economics*, 37(1), 1-34.
- [18] Goel, A., & Joyner, D. A. (2016). An Experiment in Teaching Cognitive Systems Online. In Haynes, D. (Ed.) *International Journal for Scholarship of Technology-Enhanced Learning* 1(1).
- [19] Grella, C. T., Staubitz, T., Teusner, R., & Meinel, C. (2016, September). Can MOOCs Support Secondary Education in Computer Science?. In *International Conference on Interactive Collaborative Learning* (pp. 478-493). Springer, Cham.
- [20] Grella, C. T., Staubitz, T., Teusner, R., & Meinel, C. (2016, September). Can MOOCs Support Secondary Education in Computer Science?. In *International Conference on Interactive Collaborative Learning* (pp. 478-493). Springer, Cham.
- [21] Johnstone, J. W. C., & Rivera, R. J. (1965). *Volunteers for learning: A study of the educational pursuits of American adults* (Vol. 4). Aldine Pub. Co.
- [22] Joyner, D. A. (2017). Scaling Expert Feedback: Two Case Studies. In *Proceedings of the Fourth Annual ACM Conference on Learning at Scale*. Cambridge, Massachusetts.
- [23] Joyner, D. (2018, June). Squeezing the limeade: policies and workflows for scalable online degrees. In *Proceedings of the Fifth Annual ACM Conference on Learning at Scale* (p. 53). ACM.
- [24] Joyner, D. A. & Isbell, C. (2019). Master's at Scale: Five Years in a Scalable Online Graduate Degree. In *Proceedings of the Sixth Annual ACM Conference on Learning at Scale*. Chicago, Illinois, USA.
- [25] Kay, J., Reimann, P., Diebold, E., & Kummerfeld, B. (2013). MOOCs: So many learners, so much potential... *IEEE Intelligent systems*, 28(3), 70-77.
- [26] Knowles, M. S. (1957). Philosophical issues that confront adult educators. *Adult Education*, 7(4), 234-240.
- [27] Knowles, M. S. (1980). *The modern practice of adult education: From pedagogy to andragogy*. Englewood Cliffs, NJ: Cambridge Adult Education.
- [28] Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 159-174.
- [29] Merriam, S. B., Caffarella, R. S., & Baumgartner, L. M. (2006). *Learning in adulthood: A comprehensive guide*. John Wiley & Sons.
- [30] National Academies of Sciences, Engineering, and Medicine. (2018). *Assessing and responding to the growth of computer science undergraduate enrollments*. National Academies Press.
- [31] Penland, P. (1979). Self-initiated learning. *Adult Education*, 29(3), 170-179.
- [32] Roberts, E. S. (2011). Meeting the challenges of rising enrollments. *ACM Inroads*, 2(3), 4-6.
- [33] Roberts, E., Camp, T., Culler, D., Isbell, C., & Tims, J. (2018, February). Rising cs enrollments: Meeting the challenges. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education* (pp. 539-540). ACM.
- [34] Sogunro, O. A. (2015). Motivating factors for adult learners in higher education. *International Journal of Higher Education*, 4(1), 22-37.
- [35] Steffens, K. (2015). Competences, learning theories and MOOCs: recent developments in lifelong learning. *European Journal of Education*, 50(1), 41-59.
- [36] Steinbach, T., White, J., & Knight, L. (2005). Encouraging Minority Enrollment in IT Degree Programs through Participatory Organizations. *Informing Science*, 1451-1464.
- [37] Whitecraft, M. A., & Williams, W. M. (2010). Why aren't more women in computer science. Making software: *What really works, and why we believe it*, 221-238.
- [38] Wlodkowski, R. J., & Ginsberg, M. B. (2017). *Enhancing adult motivation to learn: A comprehensive guide for teaching all adults*. John Wiley & Sons.