Hidden Costs: COVID-19's Disproportionate Impact on Underrepresented Groups in Online Computing Education

[α]Sibley F. Lyndgaard, [α]Corey E. Tatel, [α]Ruth Kanfer, [β]Julia E. Melkers, & [αγ]Justin C. Sabree

[α]Georgia Institute of Technology, School of Psychology
[β]Georgia Institute of Technology, School of Public Policy
[γ]Meta

Corresponding author: slyndgaard3@gatech.edu

Abstract. The disruptive effects of the COVID pandemic on vulnerable and/or minority demographic groups among 1) student populations and 2) persons employed in low wage sectors are well-established. This study examined whether disparity in the disruptive effects of the pandemic extend to adult learners employed in "bright prospect" sectors (e.g., computing and information technology). Survey results from a sample of 989 employees enrolled in an online Masters of Science in Computer Science program during the onset of COVID-19 revealed significant disparate impacts to work and learning as a function of age, race, and psycho-social factors (e.g., social support). The findings show that disparity in the effects of the pandemic transcend wage to affect the education and professional development of persons engaged in knowledge-based occupations. While results are based on the experiences of the COVID-19 pandemic, they provide observations and implications for navigating ongoing and future disruptive events. Specifically, results highlight the value of a 'whole-person' approach to more precisely identify the pathways by which these disruptive effects occur, particularly in the context of career development. At the institutional level, interventions to support adult learners through disruption should incorporate such an approach. Because continuous professional learning is critical for career advancement in knowledge-based sectors, the findings have implications for improving participation and mobility of underrepresented groups in computing and related fields.

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1 Introduction

Nationally, increasing numbers of U.S. adults are participating in higher education or advanced skill training, including in computing and related fields (Kasworm, 2011). In addition to the disruptions experienced as a function of clashes between work, family, and learning (Markle, 2015), adult learners are susceptible to a range of disruptive effects caused by economic, natural, and other disasters. These disruptions, which have been the subject of cross-disciplinary scholarly inquiry, vary widely in terms of duration, location, and the severity of impact to daily life. Some, like natural disasters (e.g., Lowe et al., 2015), are more localized, while others may be associated with larger-scale impacts to a specific industry (e.g., employment spikes and crashes; Lin, 2017) or even to an entire population (e.g., the 2008 recession; Simosi et al., 2015). The COVID-19 pandemic is larger in impact still, distinguished by the presence of effects that are both global and have intersectional effects across multiple domains of adult life (e.g., work, family).

Considerable evidence has accumulated documenting the negative impact of the COVID-19 pandemic on the employment and well-being of low-wage sector workers, many of whom are women and/or members of minority racial and ethnic groups (Kramer & Kramer, 2020; Tai et al., 2021). The implicit assumption made in many of these studies is that the negative effects of the disruption on these groups is primarily a function of the consequences of inadequate finances (e.g., access to healthcare, housing). However, it is also possible that there has been selective negative impact in the relatively higher-wage sector of science, technology, engineering, and mathematics (STEM) as well, particularly with respect to women and members of underrepresented groups seeking to advance their career through graduate education. Highlighting the critical influence of context on disruption during the pandemic, for example, Walsh et al. (2021) found that female and racial/ethnic minority graduate students and faculty reported difficulties during the pandemic that were inherently tied to aspects of their personal identity and background. The

current study focuses on selective impacts of the pandemic on students pursuing an online master's degree in computer science, a field for which investments in advanced professional education have implications for the participation of underrepresented groups and for long-term economic well-being (Black & Lynch, 2004; Brynjolfsson & Saunders, 2009; Doerschuk et al., 2016; Fountain, 2000). We suggest that online forms of advanced education have particular potential for ameliorating inequities in computer science and related fields, find that learners who belong to minority racial groups in the U.S. report adverse disruptive impacts during the pandemic, and posit that these results have implications for institutions and educators developing online graduate or professional STEM education.

We adopt a "whole-person" approach to examine the impacts of disruptions faced by adults engaged in online computing education. Similar frameworks have been used in careers research, where "person-centered" approaches acknowledge that social, historical, and cultural contexts interact with individual developmental trajectories to influence career-related behaviors and decisions (Vondracek & Porfeli, 2002; Zacher & Froidevaux, 2021). The whole-person approach is also similar to the concept of 'human-centered design' frequently adopted by Human-Computer Interaction (HCI) and education researchers (Hanington, 2010; Zoltowski et al., 2012). Human-centered design acknowledges the multitude of ways in which human users experience technology, with education researchers translating this approach into personalized content delivery (e.g., Baran & AlZoubi, 2020).

Consistent with this paradigm, our whole-person perspective on adult online learning considers multiple domains of life that place time or attentional demands upon the working adult. For this population, work and home are traditionally the primary domains which demand significant personal resources. Adults engaged in work-related learning add a third domain of demands. We seek to obtain a better understanding of how the intersectionality of work, non-work, and learning impact adults' ability to manage disruptive events. We also consider (1) overrepresentation of women and racial or ethnic minorities in low wage sectors and (2) historical underrepresentation of these groups in STEM at all stages of the education-to-career pipeline to be important contextual factors influencing our whole-person perspective. These issues are discussed in turn below. We then introduce online graduate education as a potential solution to pipeline issues observed in CS and related fields and introduce the current study, which investigates the extent to which major disruptions may again introduce sources of inequity to professional education in computing and related fields.

2 Review of Related Literature

2.1 **Vulnerability to Disruption: Beyond Wage and Occupational Sector.** Many existing studies on the disparate effects of the COVID-19 pandemic have focused on people working in low wage sectors, which disproportionately employ older workers, minorities, and women (Hibel et al., 2021; Janssens et al., 2021, Kramer & Kramer, 2020; Tai et al., 2021). Yet, while these lower-wage populations are among the most vulnerable to disruptive events (Ezell et al., 2021), higher-wage workers are not immune, nor are those in industries that may appear at face value as more resilient to virtual work transitions (e.g., Information Technology [IT]; Bai et al., 2021). It could be argued that global disruptions are less likely to have disparate impact across demographic groups within high-status sectors, where most individuals are expected to have access to relatively high incomes and associated resources (Noonan, 2017). In contrast, however, we suggest that disparities can be identified even in relatively high-status sectors. For individuals who are underrepresented in high-wage sectors (e.g., women and under-represented minority groups, who represent approximately 25% and 10%, respectively, of the United States STEM workforce; Beedle et al., 2011; National Research Council, 2011), defining vulnerability based only on wage level risks exacerbation of achievement gaps and threatens efforts to promote equitable representation in "bright-prospect" industries (i.e., industries which are anticipated to continue providing sustainable wages and secure employment opportunities; e.g., Briggs, 2017).

2.2 **Underrepresentation and the STEM Pipeline.** The lack of attention to the needs of underrepresented groups in higher-wage sectors, such as computing, may contribute to adverse impact on these groups' access to professional training and longer-term career development. Existing research has primarily examined these issues in terms of the "leaky pipeline" phenomenon (e.g., Almukhambetova et al., 2021; Liu et al., 2019), where increasing proportions of women and racial or ethnic minorities abandon the pursuit of STEM careers as they progress through their education and early career stages (Linnenbrink-Garcia et al., 2018). In particular, much attention is paid to retention of underrepresented groups within STEM curriculum at the secondary and undergraduate levels (e.g., Hernandez et al., 2013; Hunt et al., 2021). In the context of computing pipeline diversity, we posit that (online) graduate education represents a particularly crucial point in the computing pipeline which offers untapped potential for improving equitable outcomes within computing professions. At the same time, major disruptions experienced during this point of professional development can be expected to hinder efforts at enhancing diversity in bright-prospect STEM-related fields such as computer science. In this section, we summarize research related to when and why women and

underrepresented minorities exit the STEM pipeline, identify graduate education as a particularly critical point in the computing pipeline, and argue that disruptive effects of the pandemic on computer science online graduation students may transcend wage and occupational sector[1].

2.2.1 ***Attrition in K-12, Undergraduate, and Graduate STEM Education.*** Small differences in the numeric and spatial abilities required by STEM disciplines favoring males and majority ethnic groups at the earliest stage of education (see, e.g., Penner & Paret, 2008) may be exacerbated by later unequal access to STEM-related educational opportunities (e.g., high-quality STEM teaching, family members working in STEM occupations; Grandy, 1994; Oyana et al., 2015; Tsui, 2007). Teachers are less likely to recommend students from underrepresented groups for advanced science and math courses than their majority group counterparts (Campbell, 2012; Turetsky et al., 2021), with potentially substantial cumulative effects on educational and career trajectories. As a consequence of limited early access to advanced courses, women and underrepresented minorities are less likely than their white male peers to enroll in and complete Advanced Placement (AP) courses including math and science (Klopfenstein, 2004; Taliaferro & Decuir-Gunby, 2008). This is particularly concerning given that AP test scores afford incremental validity in the prediction of college grade-point average and STEM major persistence over and above traditional assessments such as the SAT (Ackerman et al., 2013).

In undergraduate education, women and underrepresented minorities who have declared a computer science as a major less likely than their majority group counterparts to graduate with a computer science degree and more likely to switch to a different major (Albarakati, 2020; Stephenson et al., 2018). Despite some recent improvements in completion rates, underrepresented student groups are also still at increased risk of attrition from STEM graduate programs (Sowell et al., 2015). Potential explanations for these differences in attrition rates at the university level and beyond include both academic (e.g., access to high-quality undergraduate research opportunities) and interpersonal (e.g., access to social capital) (Russell et al., 2020) factors. Lack of exposure to advanced material in K-12 education, for example, may leave students from underrepresented groups unprepared for the requirements of undergraduate STEM course work (Rothwell, 2013). Chang et al. (2011) found that men and majority ethnic-group students are more likely than women and underrepresented minorities to enroll in more advanced levels of STEM coursework, which is in turn associated with lower STEM attrition. Barriers to persistence reported by students from underrepresented groups enrolled in graduate-level STEM programs often include a lack of social capital, program-based support, and sense of belonging to the program or institution (Bancroft, 2013; Burt et al., 2018).

2.2.2 **Attrition in the STEM Workforce.** Glass et al. (2013) found gender to be negatively associated with STEM work, with women in the STEM workforce more likely to leave their chosen field than women in the non-STEM workforce. To date, however, less systematic attention has been directed to understanding the multiple factors that influence post-graduate attrition from STEM jobs. Some have explained women's exit from the STEM workforce in terms of an "opting-out narrative," which suggests that women leave their STEM jobs to accommodate competing family responsibilities (Kahn & Ginther, 2017). Although research does suggest that marriage and the birth of a child are strong predictors of labor force participation among women employees (Long, 2001; Xie & Shaumann, 2003), and that family/caregiving obligations may be associated with employment status among women of color employed in STEM fields (Fouad & Santana, 2017), a closer look at the data indicates that additional factors may account for high levels of attrition among those employed in STEM sectors, including insufficient social and environmental support provided to women in STEM work environments and/or insufficient support received from family and friends. Such social support may be critical in allowing women to cope with the competing demands of family and career responsibilities associated with the high work demands in STEM occupations (Buse et al., 2013; Fouad et al., 2011). Again, women of color in particular may experience greater social barriers to persistence in STEM careers, with subsequent impacts on development of a professional identity and retention in the STEM workforce (Duran & Lopez, 2015).

2.3 **Mitigating Pipeline Attrition Through Graduate Education.** The rapid rate of change in STEM fields has highlighted the importance of graduate education to maintain employability and promote career progress. However, the data that exists to date show that despite its criticality for STEM career development, far fewer women and underrepresented minorities participate in this level of professional development in fields such as computer science and engineering than in K-12 and undergraduate education in the same fields (Strayhorn, 2010; Miner, 2019; National Science Foundation, 2019). As the demand for STEM-related skillsets and lifelong learning has increased (Kanfer & Blivin, 2019), universities have partnered with massive online open course (MOOC) platforms (e.g., Coursera,

[1] While we are primarily interested in computing science education and the computing workforce, we draw on research that addresses the complexity of underrepresented groups' attrition in STEM broadly due to the limited number of investigations conducted using only computer science samples.

Udacity) to offer advanced degree programs in STEM areas that combine the best of both worlds – the rigor of a university degree program with the scalability of a MOOC (Duncan et al., 2020).

Interestingly, online graduate degree programs are not serving simply as an online alternative to traditional degree programs – they appear to be serving different populations. Evidence suggests that online graduate education is reaching a previously untapped educational market: Mid-career adults who would not have otherwise pursued an advanced degree (Goodman et al., 2019). Features that may be attractive to this previously untapped populations of learners include (1) affordable tuition at a greatly reduced price relative to traditional graduate training (Deming et al., 2015; Park et al., 2020), and (2) flexibility as a result of the use of large-scale online instructional methods (Joyner et al., 2019; Leasure et al., Kavlie, 2018; Ou et al., 2019). By improving access to advanced education via affordable tuition and flexible delivery, online graduate education may conceivably increase the number of individuals from underrepresented groups who earn advanced STEM degrees and thereby provide a means by which to counteract one level of the "leaky pipeline". We posit that the benefits of online graduate education for STEM workforce diversity are therefore twofold: (1) Underrepresented groups currently employed in STEM fields can participate in continuing education without disrupting their careers, and (2) Underrepresented groups seeking to enter or return to a STEM field can do so via an educational pathway that is less disruptive and less cost-prohibitive than returning to undergraduate education. However, if additional barriers related to the impact of disruptive events exist for learners who belong to underrepresented groups, the cumulative negative effects on program completion or other important outcomes could negate the benefits of online graduate education. The potential nature of such disparate impact was the focus of the current study.

2.4 **Current Study.** To our knowledge, no study to date has quantitatively examined the possibility that major disruptions, such as the pandemic, may differentially disadvantage individuals from underrepresented backgrounds in their pursuit of formal professional training and career development in computer science. We posited that engagement in a 'bright prospect' occupational sector (such as computer science) may not provide adequate protection from negative impact during large-scale crisis events. We further posited that the impacts of such a crisis (e.g., the COVID-19 pandemic) differ as a function of both demographic and psychosocial factors and that if left unchecked, these impacts may collectively exacerbate computing pipeline attrition. Online graduate education represents an under-utilized means by which computing pipeline attrition can be mitigated. The current study sought to identify the nature of difficulties experienced by working adults engaged in career-related online graduate education in the computer science field and to evaluate potential differences in disruptions to work and learning experienced by individuals of differing genders and racial/ethnic backgrounds. To investigate this issue, we asked:

i. To what extent does disparity in pandemic-related disruptions exist within adults engaged in online learning in a high wage, in-demand occupational sector?
ii. In which aspects of adult professional life (i.e., work and learning experiences) are disruptions most pronounced?
iii. Which demographic groups within a sample of computer science professionals are most vulnerable to disruptions?

What we can discover in addressing these questions has implications for both the development of educational interventions as well as broader issues of computing and STEM workforce development. The findings highlight the particular importance of targeted assistance for these groups during and after large-scale disruptions.

3 Methodology

3.1 **Participants and Procedure.** Data for this study are drawn from a survey of graduate students in an online master's in computer science program (referred to below as OMSCS). The program is completely online and asynchronous, is designed for working adults, and has enrolled over 10,000 graduate students since its inception in 2013. Most courses consist of a combination of asynchronous lectures and reading assignments, project-based homework and assignments, and exams taken remotely at the learner's discretion within a given window of time (e.g., several days up to a week). Learners have access to discussion forums/platforms populated by peers and TAs, as well as regularly scheduled office hours with TAs or instructors. Because the program is intended to be taken part-time, enrollment is limited to two courses per semester (except for specific case-by-case exceptions), and typical time demands vary based on both the number of courses enrolled in a given semester as well as the specific course chosen. The survey was distributed online in April 2020 (approximately six weeks after the initial economic shutdown in the United States) and was closed in June 2020.

All U.S. citizens[2] enrolled in courses during the first academic term of 2020 (January-May) were invited to participate in the study. A total of 1668 of 5240 eligible students responded (30.77% response rate). Of these, 85 participants were removed due to low response rates (<50%) and 158 participants were removed due to implausibly fast completion times (bottom 10th percentile). Removal of these participants brought the sample total to 1425 participants whose data were included in descriptive analyses. Additional eligibility criteria were applied for later analyses.

To determine whether demographic differences existed between the final sample and removed participants, we conducted non-parametric and independent samples t-test analyses on gender, age, and race/ethnicity. Results obtained indicate no significant differences between the groups on gender ($\chi^2 = 0.03$, ns) or race/ethnicity ($\chi^2 = 0.09$, ns). Significant differences were observed for chronological age ($t = 4.65$, $p < 0.01$) such that retained participants were older (M = 33.55; SD = 8.77) than those removed (M = 30.58; SD = 7.70). This is not of particular concern because the average age of the final sample, compared to the average age of those removed, is closer to the average age of the program's total student population (M = 33.80, Goodman et al., 2019). The utilized sample was predominantly White (64.77%) and male (84.77%), and this demographic distribution is consistent with the distribution of the population of students who are U.S. citizens (Goodman et al., 2019). Table 1 provides complete demographic characteristics for the final sample. Most participants were employed full-time both prior to (91.2%) and during (88.4%) COVID-19, but many moved from a primarily on-site (i.e., in-person) position prior to the pandemic (76.8%) to a primarily remote position during the pandemic (84.6%). See Table 2 for additional descriptive data concerning participants' employment and program financing. Visual representations of the sample's age distribution, as well as the descriptive statistics in Table 2, are provided in Appendix A.

Table 1. Demographic Characteristics

Age		**Gender**			**Ethnicity**		
		Group	***N***	***%***	***Group***	***N***	***%***
Mean	34	Male	1208	84.7	White	923	64.77
Median	31.00	Female	217	15.23	Asian	266	18.67
Range	22.00-71.00				Black	53	3.72
SD	8.77				Hispanic	95	6.67
					Other	4	0.28
					2+	70	1.19

3.2 **Measures.** In this section, we describe all survey items and measures used in our analyses. Given that the study took place during the beginning of the unprecedented disruption of the pandemic, a series of locally developed measures were created to assess the disruptive impact of the COVID-19 pandemic on behaviors and attitudes related to work and learning. The measures fall into four categories: COVID-19 impact measures, demographic variables, contextual variables, and psychological variables. COVID-19 impact measures assessed the impact of the pandemic on attitudes and behaviors related to work and learning, contextual variables assessed situations relevant to work and learning (e.g., organization type, source of tuition funding), and psychological variables assessed participants' perceptions of access to varying coping resources (e.g., social support, facilitation of transition to remote work). Example items for each scale are reported below and the full scales can be found in Appendix B.

[2] Although the program enrolls international students and permanent residents in addition to U.S. citizens, the nature of our Institutional Research Board approval restricted recruitment and analysis to U.S. citizens not currently residing in the European Union (to abide by EU data privacy restrictions). The demographics of the current sample are representative of the population of enrolled students who are U.S. citizens but may not reflect demographics of the total program enrollment.

Table 2. Employment, Working Conditions, and Program Financing

	N	%		N	%
Organization Size			**Organization Type**		
1-49	104	7.30	Private Firm	1043	73.19
50-999	287	20.14	Government	173	12.14
1000-4999	176	12.35	Non-profit	71	4.98
5000-9999	101	7.09	Self-employed	13	0.91
10,000 or more	611	42.88			
Program Financing			**COVID-19 Employment Status Change**		
Employer – full	422	29.61	No Change	1193	83.72
Employer – partial	173	12.14	Let Go/Furloughed	53	3.72
Self-Funded	771	54.11	Pay/Hours Reduced	90	6.32
Student Loans	21	1.47	Changed Jobs	24	1.68
Other	38	2.67	Other	65	4.56
Working Remote Prior to Pandemic			**Working Remote During Pandemic**		
Yes (3+ days/wk)	330	23.16	Yes	1206	84.63
No (0-2 days/wk)	1095	76.84	No	96	6.74
Employment Status: Prior To COVID			**Employment Status: During COVID**		
Full-Time	1306	91.65	Full-Time	1259	88.35
Part-Time	47	3.30	Part-Time	43	3.02
Not Employed	72	5.05	Not Employed	123	8.63

3.3 COVID-19 Impact Measures.

3.3.1 ***Work Engagement.*** An eight-item scale was developed to assess the extent to which the pandemic had disrupted participants' work engagement or motivation. Participants indicated the extent to which they agreed with the statements provided on a six-point scale ranging from "Strongly disagree" to "Strongly agree". An example item from this scale is "Since COVID-19 began, I feel less engaged in my work". The internal consistency reliability estimate of this scale was $\alpha = 0.80$.

3.3.2 ***Job Insecurity***. A four-item scale was constructed to investigate the influence of the pandemic on job insecurity. Respondents indicated the extent to which they agreed with each statement on a six-point scale ranging from "Strongly disagree" to "Strongly agree". An example item from this scale is "Since the COVID-19 disruption began, I have experienced anxiety about keeping my job". The internal consistency reliability estimate of this scale was $\alpha = 0.86$.

3.3.3 ***Online Learning Activity Management***. A four-item scale was developed to measure the extent to which the pandemic had affected student learning activity management. Participants indicated the extent to which they agreed with each statement on a six-point scale ranging from "Strongly disagree" to "Strongly agree". An example item from this scale is "Since COVID-19, I have had less time to complete my OMSCS work". The internal consistency reliability estimate of this scale was $\alpha = 0.84$.

3.3.4 ***Program Commitment***. A five-item scale was used to measure the influence of pandemic-related disruption on student commitment to the learning program. The scale provided respondents with three statements and prompted them to indicate the extent to which they agreed with each statement using a six-point scale ranging from "Strongly disagree" to "Strongly agree." An example item from this scale is "The COVID-19 disruption has caused me to put

OMSCS on the back burner" (reverse-scored so that high levels of agreement indicated lower levels of commitment). The internal consistency reliability estimate of this scale was α = 0.78.

3.4 **Demographic Variables.** Demographic variables (age, gender, and ethnicity) were obtained from participants' archival program application data.

3.5 **Contextual Variables.**

3.5.1 ***Organization Type***. Organization type was measured with a single item in which respondents indicated whether their employer was classified a private firm, government, non-profit, or whether they were self-employed. The most common organization type (N = 1043, 73.19%) was private firm. A full summary of participant responses to this item can be found in Table 2.

3.5.2 ***Organization Size.*** Organization size was measured with a single item, where respondents indicated whether their organization consisted of 1-49, 50-999, 1000-4999, 5000-9999, or 10,000 or more employees. The most common organization size (N = 611, 42.88%) was 10,000 or more. A full summary of participant responses to this item can be found in Table 2.

3.5.3 ***Hours Worked Per Day***. Respondents indicated the approximate number of hours they worked on a typical workday. Responses were restricted to between one and 12 hours and the average response was 8.44 hours (SD = 1.38).

3.5.4 ***Program Finance***. A single item was used to assess how students financed program tuition. The item asked: "Which of the following best describes how you finance your OMSCS tuition?" Participants were selected one of the following response options: "I pay using my own funds", "I pay using student loans", "My employer pays my tuition", and "Other". Self-funding was the most common response (N = 771, 54.11%). A full summary of participant responses to this item can be found in Table 2.

3.6 **Psychological Variables.**

3.6.1 ***Social Support***. A seven-item measure was used to assess the aggregate level of perceived professional and personal support for continued program enrollment that respondents received since the pandemic began. Responses were recorded in a five-point scale ranging from "Much less supportive" to "Much more supportive". Each item (e.g., "spouse", "coworkers") was preceded by the following stem: "Since the pandemic began, how supportive have the following people been of your continued enrollment in OMSCS?". The internal consistency reliability estimate of this scale was α = 0.87.

3.6.2 ***Peer Relations***. A three-item measure was used to assess the role that program peers have played in helping respondents manage the pandemic disruption. One item focused on the extent to which communication had changed since the beginning of the pandemic ("I have used the online learning forums more"). The other two items assessed the benefits of such communication ("It was helpful to discuss what is happening with my OMSCS peers", "Having OMSCS peers to talk to has helped reduce my work anxiety"). Responses were recorded on a six-point scale ranging from "Strongly disagree" to "Strongly agree". The internal consistency reliability estimate of this scale was α = 0.73.

3.6.3 ***Remote Transition***. At the time of the survey, participants were asked whether or not they were correctly working remotely (1206 or 92.63% were working remotely, 96 or 7.37% were not working remotely). For participants who were working remotely, an eight-item measure was used to assess the extent to which participants perceived that their enrollment in an online learning program facilitated their transition to remote working. Responses to each item were provided in a six-point scale ranging from "Strongly disagree" to "Strongly agree". An example item from this scale is "Learning online (in OSMCS) has made the transition to remote work easier". The internal consistency reliability estimate of this scale was α = 0.92.

4 Results

Study results are presented in three sections. First, we summarize descriptive statistics and intercorrelations among the COVID-19 impact variables and psychological variables. Descriptive statistics for demographic and contextual variables are not included here because they are presented in full in Tables 1 and 2. Next, we present results of latent profile analysis to identify differential COVID-19 disruptions based on four indicator variables (job insecurity, disruption of work engagement, disruption of learning management, and program commitment). Finally, we enter demographic, contextual, and psychological variables into a series of binary logistic regressions to identify person-level characteristics that are associated with a greater risk factor of membership in the more severely impacted profile.

4.1 **Summary Statistics and Inter-scale Correlations.** Descriptive statistics for all COVID impact variables (job insecurity, disruption of work engagement, disruption of learning management, and program commitment) and psychological variables (social support, peer relationships, and remote work transitions) are presented in Table 3. Correlations between these variables (see Table 4) range from -0.72 to 0.47, with most (19 out of 21) falling between -0.30 and 0.30.

Table 3. Scale Descriptive Statistics

	N	Mean	Median	Range	SD
COVID-19 Impact Variables					
Job Insecurity	1302	2.67	2.50	1-6	1.18
Work Engagement Disruption	1300	3.60	3.62	1-6	0.95
Online Learning Mgmt Disruption	1262	3.32	3.25	1-6	1.32
Program Commitment	1410	3.89	4.00	1-6	1.11
Psychological Variables					
Social Support	1388	3.48	3.20	1-5	0.70
Peer Relations	1261	3.12	3.00	1-6	1.05
Remote Work Transition	1199	3.75	3.88	1-6	1.05

Note. All descriptive scale statistics were calculated using the full sample (n = 1425). However, some participants did not complete portions of the survey (e.g., unemployed participants did not complete the work engagement disruption scale) and were excluded from this analysis for measures they did not complete.

Table 4. Correlations Between Psychological and COVID-19 Impact Variables

	1	2	3	4	5	6	7
Social Support	1						
Peer Relations	0.211***	1					
Remote Work Transition	0.174***	0.740***	1				
Job Security	-0.047	0.121***	-0.011	1			
Program Commitment	0.150***	-0.017	0.206***	-0.237***	1		
Work Eng. Disruption	-0.026	0.099***	-0.047	0.254***	-0.280***	1	
Learning Management Disruption	-0.061*	0.244***	-0.009	0.243***	-0.719***	0.252***	1

Note. *p < .05, ** p < .01, *** p < .001. Each pairwise comparison used only complete cases for the two relevant variables. Ns for individual correlations ranged from 1054-1410.

4.2 **Latent Profile Analysis.** Latent profile analysis (LPA) is a person-centered approach that identifies 'profiles' of latent group membership based on a set of continuous indicator variables (Hofmans et al., 2020; Howard & Hoffman, 2018). In the current study, we sought to identify profiles that differentially characterized the nature and extent of disruption experienced by participants due to COVID-19. We included indicator variables across both work (job

insecurity, disruption of work engagement) and learning (disruption of learning management, OMSCS commitment) because successful management of these domains are interrelated (Money & Dean, 2019; Wladis et al., 2015), and massive disruptions are likely to impact multiple life domains both directly and indirectly (Cho, 2020). Because our goal was to assess disruption to work and learning, we limited analyses to participants who had completed both the work- and learning-related scales. Therefore, participants who either were not employed or currently taking a course (e.g., had withdrawn earlier that semester) at the time of survey completion were not included in the analysis. The exclusion of these participants reduced the usable sample to 989 participants (86.05% male, 13.95% female, M_{age} = 33.81, SD_{age} = 8.73), and this group is used for all further analyses.

We tested potential solutions for two, three, and four profiles. Profile solutions beyond this were not considered because beyond four (the number of indicator variables included) it could not be reasonably argued that parsimony was considered in our choice of a solution. The potential solutions were compared using Akaike Information Criterion (AIC; Akaike, 1974), Bayesian Information Criterion (BIC; Schwarz, 1978), Consistent Akaike Information Criterion (CAIC; Bozdogan, 1987) fit indices, and the bootstrapped Likelihood Ratio Test (bLRT, p-values < 0.05 indicate a better-performing model; McCutcheon, 1987). AIC, BIC, and CAIC are information-theoretic methods for selecting an optimal number of profiles, while bLRT is a statistical model comparison approach assessing goodness of fit between a model of interest and a model with one fewer (i.e., K -1) profile (Tein et al., 2013). All indices considered in this study indicated that a 2-profile solution provided the best fit for our data. See Table 5 for fit indices associated with each solution and Table 6 for information on demographic information about members of each profile in the chosen solution.

Table 5. Fit Indices of Latent Profile Solutions

	bLRT	**AIC**	**CAIC**	**BIC**
2-Profile Solution	56.967*	11,166.61	11,278.65	11,259.652
3-Profile Solution	0.744	11,175.87	11,317.39	11,293.392
4-Profile Solution	1.852	11,184.02	11,355.02	11,326.024

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table 6. Profile Membership by Demographic Variables

	Non-Black/ Hispanic		**Black/ Hispanic**		**Male**		**Female**		**M_{age}**	**SD_{age}**
	N	***%***	***N***	***%***	***N***	***%***	***N***	***%***		
Profile 1 (Less Disruption)	468	90.70	48	9.30	451	87.40	65	12.60	32.84	8.40
Profile 2 (Greater Disruption)	401	84.78	72	15.22	400	84.57	73	15.43	34.87	8.96

Figure 1 presents a density plot for the two-profile solution. Density plots show profile distributions on each indicator variable and can be interpreted as showing the extent to which indicator variables drive profile membership. In the current study, Figure 1 suggests that Profile 1 (in red) is characterized by relatively low disruption to learning management and relatively high program commitment, while Profile 2 (in blue) is characterized by relatively high disruption to learning management and relatively low program commitment. As illustrated in Figure 1, the results of the LPA analyses suggest that our data are best characterized by two profiles that can be interpreted as ‘less’ (Profile 1) and ‘more’ (Profile 2) relative disruption. The findings further suggest that profile membership is primarily a function of disruption to learning and learning attitudes (rather than, e.g., job insecurity).

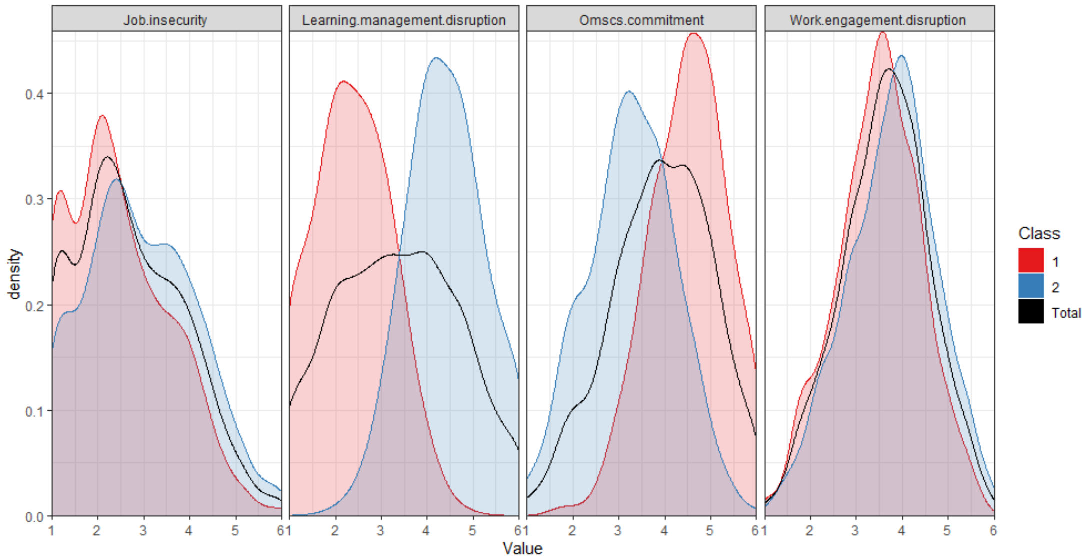

Figure 1. LPA 2-Profile Solution: Density Plot

4.3 **Binary Logistic Regression.** While our LPA findings suggest that large-scale disruptions produce disparate impact even for employed adults in higher wage sectors, these results on their own do not provide sufficient guidance for identifying at-risk populations or for mitigating the greater relative disruption experienced by such groups. To address this question, we used a series of binary logistic regression equations to interpret the unique effect of person-level characteristics (demographic, contextual, and psychological variables) on the likelihood of profile membership. Three successive models were tested. Model 1 included only demographic variables, Model 2 added a set of contextual variables (organization type, organization size, source of funding, and hours worked per day), and Model 3 added a set of psychological variables (social support, peer relationships, and ease of remote work transition). For each categorical variable, the most frequently observed level was chosen as the reference group (Garson, 2012; see Table 7 for more details). To test the incremental predictive ability of the three models, we conducted an Analysis of Deviance test between Model 1 and Model 2 (Δ residual deviance = -36.159, $p < 0.001$) as well as between Model 2 and Model 3 (Δ residual deviance = -52.412, $p < 0.001$). Results show that each sequential addition of variable sets significantly improved predictive ability of the model. A summary of these model comparison tests, along with alternative fit indices for each model (Log Likelihood, AIC, CAIC, BIC) are presented in Table 8.

In the final model, significant predictors of membership in the more severely affected profile include demographic, contextual, and psychosocial variables. In accord with historical underrepresentation of Black and Hispanic individuals in computer science and related fields (Varma, 2006; Whitney & Taylor, 2018), we recoded ethnicity from a six-category variable to a binary variable (Black/Hispanic, Not Black/Hispanic). Participants who were Black or Hispanic ($b = 0.556$, $z = 2.620$, $p < 0.01$) and older ($b = 0.031$, $z = 3.737$, $p < 0.001$) were more likely to be fall within the severely affected profile by a factor of 1.743 and of 1.031 (per year) respectively. The only significant contextual predictor was hours worked per day on average ($b = 0.291$, $z = 5.276$, $p < 0.001$), with each additional hour increasing the likelihood of severe disruption by a factor of 1.338 per additional hour. Finally, significant psychological predictors of membership in the more severely disrupted profile included having less social support for continued enrollment in the program ($b = -0.274$, $z = -2.594$, $p < 0.01$), reporting a more difficult transition to remote work ($b = -0.249$, $z = -3.311$, $p < 0.001$), and relying more on peer relationships ($b = 0.539$, $z = 6.810$, $p < 0.001$). For every one-unit increase in social support for continued enrollment and in the reported ease of the transition to remote work, the likelihood of being in the more severely affected profile decreased by a factor of 0.760 and 0.780 respectively. For every one-unit increase in reliance on peer relationships, the likelihood of being in the more severely affected profile increased by a factor of 1.714.

Table 7. Binary Logistic Regression: Model Summaries

	Model 1			Model 2			Model 3		
	b	*Z*	*OR*	*b*	*Z*	*OR*	*b*	*Z*	*OR*
Intercept	-1.196	-4.430	.302	-3.495	-6.539	0.030	-3.484	-5.128	.031
Demographic									
Female	.290	1.541	1.336	.322	1.677	1.380	.382	1.931	1.467
Black/Hispanic	.585	2.916^{**}	1.795^{**}	.563	2.736^{**}	1.756^{**}	.556	2.620^{**}	1.743^{**}
Age	.030	3.904^{***}	1.030^{***}	.027	3.356^{***}	1.027^{***}	.031	3.737^{***}	1.031^{***}
Contextual									
Org Type									
Government				-.017	-.078	0.983	.031	.138	1.032
Self-employed				.636	.872	1.890	.615	.840	1.850
Non-profit				-.075	-.261	0.928	-.045	-.152	0.956
Org Size									
5000-9999				.200	.772	1.221	.278	1.045	1.320
1000-4999				.119	.578	1.126	.173	.819	1.189
50-999				.012	.068	1.012	.084	.471	1.088
1-49				-.013	-.047	0.987	.283	.171	1.050
Program Financing									
Fully employer				-.213	-1.364	0.809	-.206	-1.285	0.814
Partially employer				-.094	-.461	0.911	-.115	-.548	0.892
Student loans				.571	.801	1.770	.401	.544	1.494
Other finance				.136	.305	1.146	.035	.077	1.036
Hours Working				.291	5.426^{***}	1.337^{***}	.291	5.276^{***}	1.338^{***}
Psychological									
Social support							-.274	-2.594^{**}	0.760^{**}
Peer relations							.539	6.811^{***}	1.714^{***}
Remote transition							-.249	-3.311^{***}	0.780^{***}

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. Profile 1 (Less Relative Disruption) was used as the reference group for latent profile. Reference groups were chosen based on the majority response within the sample, and were as follows for gender, ethnicity, organization type, organization size, and program financing: Male, Not Black/Hispanic, Private firm, 10,000, and Self-funded. N = 989 for all models.

Table 8. Binary Logistic Regression: Model Comparison

	Model 1	Model 2	Model 3
Fit Indices			
AIC	1352.181	1340.011	1293.603
Null deviance	1369.175	1369.175	1369.175
Residual deviance	1344.181	1308.011	1255.603
Model Comparison			
Δ Residual deviance		-36.159^{***}	-52.412^{***}

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

5 Discussion

The global pandemic has had far-reaching effects on individuals in all walks of life, with often devastating effects on economically vulnerable individuals. Our findings extend this line of research by showing that inequities in negative impacts persist among individuals in higher wage sectors, particularly among older persons and persons in underrepresented racial/ethnic groups. In a sample of working adults enrolled in an online master's program in computer science during the onset of the global health crisis, we identified two profiles of COVID-19 disruption across the work and learning domains that differed in relative severity. Ultimately, our findings highlight inequitable impacts of major disruptions which may impact diverse groups of working adults using computer-based learning to advance their careers or professional development goals. We identified key demographic/contextual variables which were predictive of disruption intensity: People of color, older learners, and those who work longer days on average were more severely disrupted. Social context and support structures also mattered: Participants with less social support, greater reliance on peer relationships within the learning program, and those who reported more difficult transitions to remote work were more likely to show greater COVID-19 disruption. Our findings on adult learners' reliance on social support and peer relationships are consistent with a recent study on undergraduates' experiences with rapid transitions to remote learning early in the pandemic, where the absence of such support was associated with greater feelings of isolation (Cho et al., 2021). Unexpectedly, however, gender did not emerge as a predictor of more severe disruption. These results stand in contrast to recent evidence and views about the uneven burden of caregiving that an unanticipated disruption places on women and men and the implications such inequities are observed to have for work and professional development (Alon et al., 2020; Krukowski, et al., 2021). Below, we discuss potential reasons for this unexpected finding and suggest that future research is needed to clarify this result.

It is important to note that the major driving factor of membership in the more severely disrupted profile seemed to be learning-related rather than work-related: Those in the more disrupted group reported more difficulty in managing their learning time and lower commitment to the program. Under intense environmental pressure, the cascading effects on the interrelated domains of learning, work, and home appear to put learning (and therefore professional/personal development critical for career advancement) at primary risk. Further, the risk is greater for Black and Hispanic individuals in this sector. This finding is particularly important given the tendency of global disruptions to act as a catalyst for technological advances and workplace automation (Kanfer et al., 2020), thereby increasing pressure on individuals to pursue education or skill training to bolster employability (Hershbein & Kahn, 2018; Kizilcec et al., 2021). In other words, we find that disruptions may threaten the utility of online education to meet growing demands of the skill marketplace for underrepresented groups, for whom learning may be the first domain to face pressure. Consistent with recent findings by Walsh et al. (2021), our results show that negative impacts of the pandemic are not limited to persons employed in frontline, low-wage sectors, but also occurred among underrepresented groups in a higher SES occupational sector. Using a larger sample and quantitative analyses, our findings support and extend Walsh et al.'s (2021) findings and further suggest that the more disruptive effects of the pandemic on underrepresented groups in bright prospect sectors may be more widespread than initially expected across industry sectors.

Overall, our study makes two important contributions. First, we identify risk factors associated with greater susceptibility to disruption in online computing education. Of potentially greatest importance, our findings suggest that disruptive experiences may impede career development among older employees and working adults who belong to underrepresented groups in STEM. At the institutional level, a better understanding of the "who" and "how" of disruption during online computing education could inform the development of interventions to reduce the risk of attrition and improve long-term career development for underrepresented groups. This aligns with a growing corpus of work in other knowledge-based industries, for example the research and academic community, where younger employees and women have experienced considerable challenges, threats to well-being and diminished productivity during the pandemic (Barber et al., 2021; Krukowski et al., 2021; Myers et al., 2020). Our findings are particularly well aligned with prior research emphasizing the important role played by social support in mitigating negative learning experiences (Cho et al., 2021; Giancola et al., 2009; Walsh et al., 2021).

Second, our "whole person" approach highlights the deeply connected nature of personal and professional life roles, and the pathways by which underrepresented group membership may hinder advancement and well-being irrespective of industry. In the case of IT, with its continuous learning requirement, the balance between work and non-work demands may be more easily disrupted among individuals with fewer readily available resources by which to cope with disruptions (Estrada et al., 2016). Taken as a whole, our findings indicate that the negative impacts of global disruption are not limited to persons in low-wage or at-risk occupational sectors, but are better understood in terms of the individual as a "whole" and his/her social, economic, and psychological resource for mitigating the negative impacts of global disruptions.

5.1 **Limitations and Future Directions.** An important qualification on our findings is that our research occurred relatively early in the pandemic and does not capture the rapidly changing nature of the context surrounding the pandemic. Our survey captured a period during which economic, social, and public health conditions were shifting daily, leading to a reasonable expectation that longitudinal data (or even cross-sectional data collected at a different time point may have shown meaningfully effects. Because our data collection was restricted to U.S. citizens, we also do not capture conditions of the pandemic as it was occurring elsewhere in the world during the first half of 2020. We suggest that while this does not detract from the implications of the study as they are discussed here, it does warrant caution about generalizing our findings to international populations. Likewise, while our sample offered an ideal context in which to examine the intersection of work, home, and learning, it is specific to the IT industry and therefore relatively homogenous. This homogeneity may explain, for example, the unexpected lack of a significant gender effect on disruption severity, given the underrepresentation of women in our sample. While our sample is highly representative of the study population (i.e., all U.S. citizens enrolled in the learning program), it is not representative of the larger American workforce and therefore has limited generalizability. Again, this may reflect historical and cultural idiosyncrasies about occupation-specific employment trends in the U.S. (Varma, 2006; Whitney & Taylor, 2018). While underrepresentation of women in computing and other related fields is certainly not limited to the U.S. (e.g., Huyer, 2019), we encourage future research to address this either by sampling from more demographically diverse populations, or by using sampling methods (e.g., stratified random samples) that would guarantee more equal representation across groups of interest.

Future research might also build on our findings by investigating the mechanisms through which the direct effects observed in this study occur. For example, researchers interested in individual differences in responses to distressing events such as COVID-19 might investigate age-related developments in emotion regulation skills (e.g., Blanchard-Fields, 2007) as a potential mediator between age and negative affect. Increased disruption of work-learning-life management for underrepresented groups is a potential barrier both for the entry of diverse learners into professional education as well as for persistence within the learning program.

From a career perspective, the accumulation over time of small group differences in learning disruptions may lead to exacerbation of inequities currently observed in IT and related fields (e.g., representation; Whitney & Taylor, 2018; access to future learning and/or advancement opportunities, Armstrong et al., 2018; Roldan et al., 2004). Future research should continue to consider how global disruptions alter working adults' pursuit and strategic management of professional education and training in computing and related industries as an important part of career development, and how differences in access to support or other psychosocial resources could mitigate these effects. Despite a recognized need for organizational investment in reskilling (Agrawal et al., 2020; Illanes et al., 2018), for example, organizations in the throes of an economic downtown may be less willing to invest in programs like tuition reimbursement, removing a primary means of financial support for individuals interested in pursuing additional education. Given our finding that individuals who were more reliant on peer support were more likely to be in the severely impacted profile, researchers interested in educational policy might investigate whether interventions designed to facilitate peer communication (e.g., computer-supported collaborative learning, Jeong et al., 2019) could improve outcomes for at-risk learners (e.g., reducing program attrition). Finally, when possible, studies assessing the impact of large-scale disruptions should aim to incorporate longitudinal data that captures the dynamic and uncertain nature of such events.

6 Conclusion

Our approach responds to calls to identify the effects of a global disruption on individual career management and development, especially for underrepresented groups who have historically experienced disparate impact from such events (Cho, 2020; Restubog et al., 2020). Taking an integrative, 'whole-person' approach underscores the point that certain (often underrepresented) demographic groups' vulnerability to global disruption events is not limited to low-wage occupational sectors. Indeed, our findings suggest that such an integrative approach is critical for understanding and mitigating the impact of global disruptions on diverse groups pursuing online education, including those in occupations requiring advanced degrees and training. Further, because pandemic-related disruptions are likely to accumulate over time and differ as a function of personal resources (Akkermans et al., 2020; Thomas et al., 2020), unchecked disparity in this and similar "bright-prospect" sectors may have increasingly severe consequences for the retention of underrepresented groups in these sectors. In the long-term, our findings support the development of targeted inventions that facilitate underrepresented group members' completion of development programs critical for career advancement. Prescient perspectives have suggested that online learning could be critical during disasters or other disruptions when in-person educational operations are interrupted (Smith et al., 2008). As institutions continue

to prioritize and develop online learning, we urge administrators and educators to consider whether their programs contain infrastructure to mitigate adverse impact of disruptive events.

7 Declarations

Ethics Approval. This research and its associated informed consent form was pre-approved by the Georgia Institute of Technology Institutional Review Board, protocol No. H17076.

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Data Sharing. The data that support the findings of this study may be available from the project principal investigator [JM] on reasonable request and subject to IRB guidelines. The data are not publicly available due to consideration of participant privacy and because active research under Alfred P. Sloan Foundation Grant No. G-2019-12499 is ongoing.

Authors' Contributions. Contributions are indicated by author initials below. Order in each contribution based on final author order of paper. *Conceptualization*: SL, CT, RK, JM. *Materials Preparation*: All authors. *Data Collection*: SL, CT, RK, JM. *Data Cleaning and Analysis*: SL, CT, JS. *Writing - original draft preparation*: SL, CT. *Writing - review and editing*: All authors. *Pre-submission approval check and edits*: All authors. *Supervision*: RK, JM

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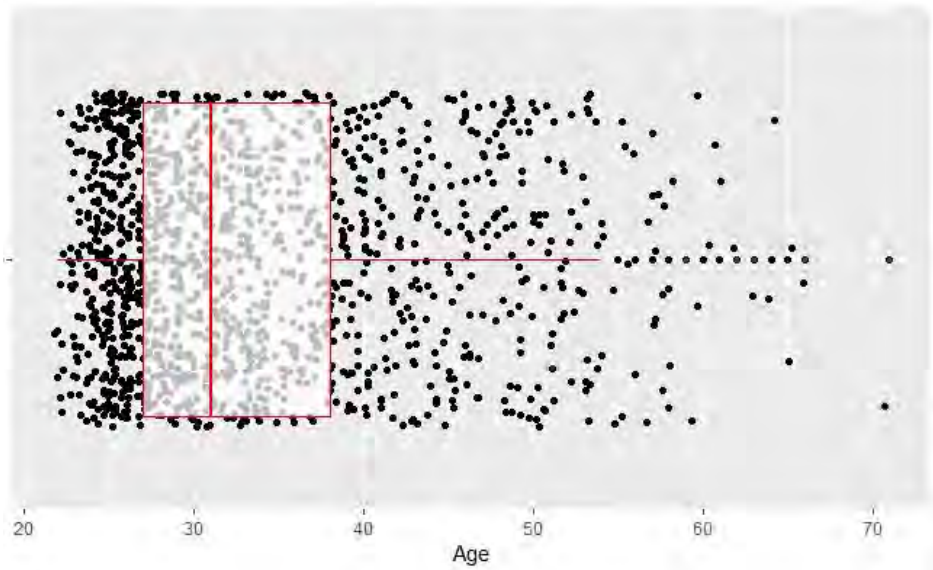
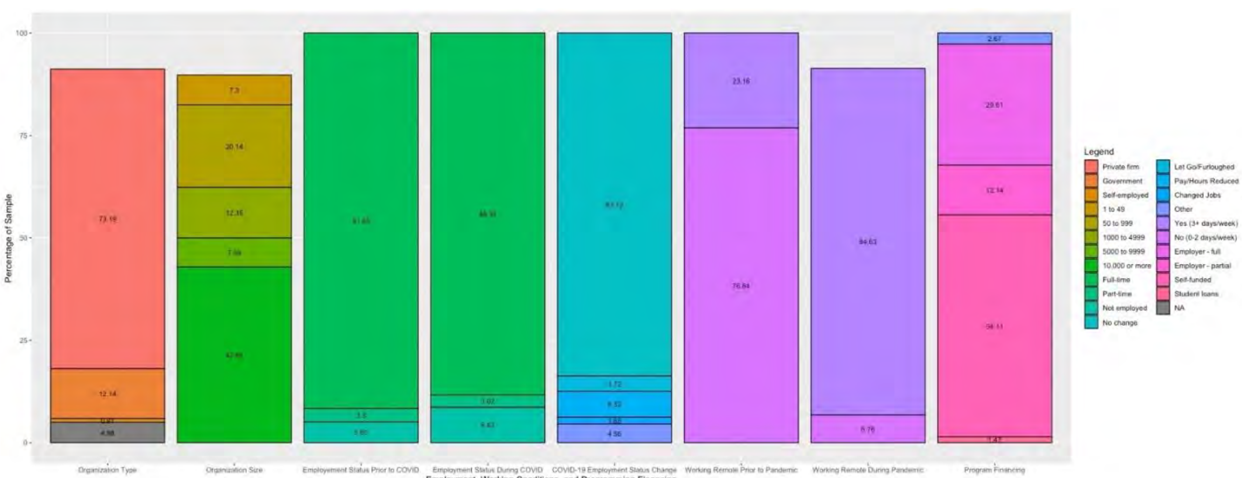
Appendix A. Distribution of Participant Ages (a) and Descriptive Statistics for Participants' Employment and Program Financing (b).



(a)



(b)

Appendix B. Survey Measures of Pandemic Disruption

Work Engagement *Since COVID-19 began…*[a]	**Job Insecurity** *Indicate your agreement with each statement about your current job*[a]
I feel less engaged with my work	Chances are that I lose my job in the near future
I do less socializing (online) with my coworkers	I feel insecure about my employment future
I feel less connected to my organization	I think I might need to look for a new job soon
I have worried about feeling healthy when I return to work	*Since the COVID-19 disruption began, I have…*
I have enjoyed working remotely[*]	Experienced anxiety about keeping my job
I am eager to return to a non-remote job	
I have found myself more distracted while working	
I have felt more discouraged about my work	

Online Learning Activity Management Indicate the extent to which each of the following statements describe your experience since COVID-19 began[a]	**Program Commitment** The COVID-19 disruption…[a]
I have had less time to complete my OMSCS work	Has caused me to put OMSCS on the back burner[*]
I have turned in assignments late	Has made it harder for me to focus on my OMSCS tasks[*]
I experienced more conflict between OMSCS and my other responsibilities	Will slow down my progress toward completing the OMSCS program[*]
I have had to change the way I approach my OMSCS work	Has increased my commitment to completing the OMSCS program
	Has made my participation in the OMSCS program less importance than achieving my work goals[*]

Social Support Since the pandemic began, how supportive have the following people been of your continued enrollment in OMSCS?[b]	**Peer Relations** Indicate the extent to which each of the following statements describe your experience since COVID-19 began[a]
Supervisor	I have used the online forums more
Colleagues at work	It was helpful to discuss what is happening with my OMSCS peers
Spouse/partner	Having OMSCS peers to talk to has helped reduce my work anxiety
Child(ren)	
Other family	
Friends	
OMSCS students	

Peer Relations Indicate the extent to which each of the following statements describe your experience since COVID-19 began[a]	**Remote Transition** Learning online (in OMSCS)…[a]
I have used the online forums more	Has made the transition to remote work easier
It was helpful to discuss what is happening with my OMSCS peers	Has helped me use remote communication platforms (e.g., Webex) at work
Having OMSCS peers to talk to has helped reduce my work anxiety	Has increased my patience and discipline for working remotely

	Has helped me to communicate more effectively
	Has improved my time management skills
	Has helped me to assist my coworkers with remote work
	Will help me to keep my job
	Has improved my online communication and collaboration skills

Note. * = Reverse-scored item. [a] = Response scale ranging from "Strongly disagree" to Strongly agree". [b] = Response scale ranging from "Much less supportive" to "Much more supportive". Overall scale scores were computed as the average response. Items on the Social Support response scale also contained "I'm not sure" and "NA", which did not contribute to the overall scale score.