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Gendered Professional Role Confidence and Persistence of Artificial Intelligence and Machine Learning Students

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Abstract

Machine learning and artificial intelligence (ML/AI) technology can be biased through non-representative training and testing activities leading to discriminatory and negative social consequences. The enormous potential of ML/AI to shape the future of technology underscores the need to increase the diversity of workers within the field, with one group of untapped talent being women engineers. An unresolved contradiction exists between the trend of greater woman representation in broader STEM fields and the consistently low numbers of women engineers pursuing careers in ML/AI. Furthermore, there has been a lack of tailored research investigating the potential causes of such under-representation.

Professional Role Confidence has been shown to be a significant and positive predictor of persistence of women in STEM. However, this link has not yet been established specifically within the field of ML/AI. For this study, we surveyed targeted undergraduate students at a major international university. Students reported on their predictors of persistence including their Professional Role Confidence in ML/AI, their experiences with discrimination, their career exposure, and their internal drivers. We present three models using Ordinal Logistic Regression to determine the effect of those predictors on Intentional Persistence. We found that higher levels of Expertise Confidence and Career Fit Confidence were related to higher levels of Intentional Persistence in ML/AI careers. We also found that women who experienced discrimination from their instructors were less likely to persist in engineering and that discrimination from peers was more prevalent for women than for men. Focusing on those predictors of Intentional Persistence, our study calls for efforts to correct the under-representation of women in ML/AI.

Introduction

Machine learning and artificial intelligence (ML/AI) technology has enormous potential to impact the world around us. The creators of ML/AI technology wield the power to influence the resulting effects on the users, either positively or negatively and they are in greater demand, now more than ever [1]. In ML/AI solutions, there is a seemingly intelligent agent between the developer and the end user that makes decisions affecting the output. This model removes the developer from the output by a degree but does not remove the developer's biases that may be built into critical elements of the technology such as the training data [2]. The data can introduce racial, gender, or ideological biases into the technology [3]. Systematic biases are prevalent in ML/AI technology used in diverse applications such as facial recognition [4], legal decision-making [5], financial decision-making [6], and natural language processing [7]. Since the technology is relatively new, the associated biases are only beginning to be researched. However, the biases have a large potential impact [8].

As the field grows and creates job opportunities, more skilled workers will be needed [1]. Women represent a group of untapped talent in ML/AI. The World Economic Forum reports that only 22% of global AI professionals are women, compared to 78% men [9]. For the past four years, the percent of women in the field has only oscillated between 21% and 23%, indicating that the talent gap is not closing, and focused intervention is necessary [9].

By addressing the issue of a lack of diversity by increasing representation of groups such as women, ML/AI technology would be developed by a more representative workforce making it less prone to biases. However, there is no detailed understanding of why women are less represented in ML/AI as compared to other STEM fields. This makes it difficult to address the root cause of the issue. Understanding the early decision-making of women that prevents them from joining the ML/AI workforce will be necessary to advise future educational practices that can improve representation of women in the field.

Background

1. Diversity and Gender Representation

Diverse teams have been shown to make better decisions, think more critically about information, and come up with more innovative ideas [10]. Diversity in the workplace can lead to higher-functioning teams and greater economic advantages [11]. Minority workers in homogenous teams experience discrimination and other unequal treatments that can detrimentally affect their wellbeing [12]. Reasons like these motivate the efforts to increase diversity in fields under-representing women, which includes STEM fields.

Engineering fields have always consisted of an over-representation of men and under-representation women [13]. Since AI/ML professionals come predominantly from those fields, the specialization has inherited that same gender bias [14]. Research on women's career decisions have illuminated some influencing factors that can be leveraged in strategies for improving gender representation [15, 16]. However, there is little research on women in engineering who are pursuing a career in ML/AI. It is important to understand how the representation of women can be improved in ML/AI specifically so that strategies can be implemented earlier in the development of the emerging field.

2. Professional Role Confidence and Persistence

The concept of confidence is the belief in one's capabilities and has been studied in various educational environments as an important aspect of professional success [17, 18]. The confidence of women students in STEM is generally lower than men, a phenomenon which has been linked to the underrepresentation of women in STEM fields and has led to the educational strategies for improvement [17, 19, 20]. The confidence levels of females in STEM were investigated by Sobel et al. through data collected on the educational software tool, Piazza, and were negatively correlated to class size and were lower than those of their male counterparts [21].

Persistence refers to an individual's commitment to stay in a profession. Persistence is a measure that has been used as a direct predictor of representation of minorities, such as women, in the workplace [15]. Gendered persistence has been studied in STEM for students on track to become scientific researchers [22] and in engineers [23]. Understanding the influences that affect the lower levels of persistence of women in STEM [24] can aid in creating informed policies that improve persistence, and ultimately, diversity in the workplace. Cech et al. present an open-call to researchers to continue their research in Professional Role Confidence and persistence of engineers through exploring the concepts in different professions and investigating other possible 'determinants of persistence' [15].

This work focuses on narrowing the scope of research subjects from all engineers to engineers studying ML/AI. Students pursuing an ML/AI education are subject to a unique environment given the rapidly-growing and highly productive nature of the field. Given that ML/AI is on track to "affect all aspects of our society and life" including employment, consumerism, and connectivity [25], and has already begun to do so [26], it is worthwhile to build on the few research initiatives that investigate how education can affect the demographics of the workforce, specifically of underrepresented groups like women. Hypotheses 1a through 2b are aimed at reproducing the work done by Cech et. al [15] in a narrower field of study. They found that Expertise Confidence and Career Fit Confidence both predicted persistence and were cultivated more successfully in men than women in a sample of general engineering students from four American colleges. In this study, we are looking to reproduce those same results in a narrower sample of ML/AI engineering students at a Canadian Institution that specializes in ML/AI.

Hypothesis 1a: Expertise Confidence is a positive predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 1b: Women have less Expertise Confidence than men in ML/AI.

Hypothesis 1c: Women have less Intentional Persistence in ML/AI and engineering than men.

Hypothesis 2a: Career Fit Confidence is a positive predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 2b: Women have less Career Fit Confidence than men in ML/AI.

Beyond the measures of Expertise Confidence and Career Fit confidence described by Cech et al. [15], the concept of 'technical self-confidence' can also lead to professional success [27]. Technical self-confidence has been measured in specific STEM areas such as engineering communication [28], horticultural science [29], and in the surgical skills of senior medical students [30]. All of these studies emphasized the importance of Technical Confidence in success later on in a professional career.

Technical Confidence in the context of this research evaluates confidence in tangible technical skills that are more field-specific than the measures for Professional Role Confidence. Technical Confidence covers confidence in the specific technical knowledge of ML/AI courses as well as confidence in the fundamental skills required for an ML/AI career: computer programming, mathematics and statistics [1, 31, 32]. Hypotheses 3a and 3b follow the same logic as hypotheses 1a through 2c that asserts that measures of confidence related to skills acquired in a post-secondary education positively predict Intentional Persistence. Studies of women in the related fields of computer science have found that men report higher levels of confidence in technical skills than women [33, 34]. This finding still requires confirmation within the new field of ML/AI engineering.

Hypothesis 3a: Technical Confidence is a positive predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 3b: Women have less Technical Confidence than men in ML/AI.

3. Discrimination in University

Women in engineering consistently report experiences of discrimination during their engineering career [35 - 37]. Experiencing discrimination during the professional development of an engineering student can lead to less willingness to persist in the field, if it is perceived as a hostile environment [38]. Gender discrimination in the STEM workplace has been previously documented. According to the Pew Research Center survey in 2017, 50% of women in STEM reported that they had experienced gender discrimination at work, compared to 19% of men. Furthermore, 20% of women reported that their gender made it harder to succeed at work and 38% indicated that sexual harassment is a problem in the workplace [39]. However, fewer details are available on discrimination experienced by women in engineering during their university education. Discrimination at an earlier stage of professional development may have lasting impacts on their career decisions. Therefore, the study of discrimination at the university level should be elaborated on. We hypothesize in 4a and 4b that discrimination experienced by women in university is a significant negative predictor of Intentional Persistence.

Women in academia are under-represented at all levels, but increasingly so in more senior positions [40]. In the 2018-2019 academic year, the University of Toronto Faculty of Applied Science and Engineering reported that women made up 39.8% of the first-year students, 27.1% of the graduate students and only 15% of professors [41]. Discrimination can be perpetrated by peers as well as by those in positions of authority [37] and may be perpetrated by different groups at different rates. We hypothesize that in all cases, women in ML/AI are more likely to experience discrimination than men due to their continued underrepresentation. We have separated discrimination between university peers and university teaching staff to investigate whether authority of the perpetrator changes the effects of the discrimination.

Hypothesis 4a: Discrimination from university peers is a negative predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 4b: Women in ML/AI experience more discrimination from peers than men.

Hypothesis 5a: Discrimination from university teaching staff is a negative predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 5b: Women in ML/AI experience more discrimination from teaching staff than men.

4. Career Exposure

For women in STEM, earlier career exposure has been positively correlated to persistence in the field [42]. Exposure from a parent or close relative has also demonstrated a similar relationship [43, 44]. However, these relationships have not been shown in ML/AI specifically. Therefore, we hypothesize that those factors are both positive predictors of Intentional Persistence. Given that there are more deterrents for women to pursue ML/AI, we hypothesize that earlier or familial exposure to ML/AI is more likely for women than men.

Hypothesis 6a: Having a parent or close relative in ML/AI is a positive predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 6b: Women in ML/AI engineering are more likely than men to have a parent or close relative also in ML/AI.

Hypothesis 7a: Having a parent or close relative in a field related to STEM is a positive predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 7b: Women in ML/AI engineering are more likely than men to have a parent or close relative in a field related to STEM.

Hypothesis 8a: Early exposure to a to a potential career in ML/AI is a positive predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 8b: Women are exposed to a potential career in ML/AI later than men.

5. Internal Drivers

Internal drivers are defined here as personal characteristics that influence outward decision such as Intentional Persistence in ML/AI and engineering. Although there are many internal drivers that could potentially be considered in this study [45], we chose two that are particularly reflective of the field of ML/AI. The vast potential of ML/AI technology has resulted in its application to a variety of solutions designed for social benefits [46], such as image-processing software used in diagnostic screening to ultimately improve patient healthcare [47]. Women have traditionally shown a greater interest in work with social benefits compared to men in fields other than ML/AI [48]. This is one explanation for why women are more represented in certain areas of STEM such as the medical sciences [49] or biomedical engineering [50]. We hypothesize that an interest in work with social benefits is a positive predictor of Intentional Persistence and that women are more interested in such work.

The ML/AI industry has led to the creation of technologies built by teams looking to offer a competitive edge to the business [51]. In education, ML/AI is an increasingly popular specialization for engineering students [52]. Elements of ML/AI education that may spark competitiveness in its students are the long waitlists for courses and the financial prospects [1].

For these reasons, we hypothesize that competitive students will have higher levels of Intentional Persistence. Since women in ML/AI not only have to face the regular competitive nature of the field, but also face the gender discrimination [38] and other barriers to success due to their gender [43], we hypothesize that women in ML/AI are more competitive than men.

Hypothesis 9a: An interest in work with social benefits is a positive predictor of Intentional Persistence in ML/AI engineering.

Hypothesis 9b: Women are more interested in work with social benefits than men.

Hypothesis 10a: Competitiveness is a positive predictor of Intentional Persistence in ML/AI and engineering.

Hypothesis 10b: Women are more competitive than men in ML/AI.

Hypothesis 1 through 10 summarize the ten predictors of Intentional Persistence in both ML/AI and engineering that will be investigated as represented in Figure 1.

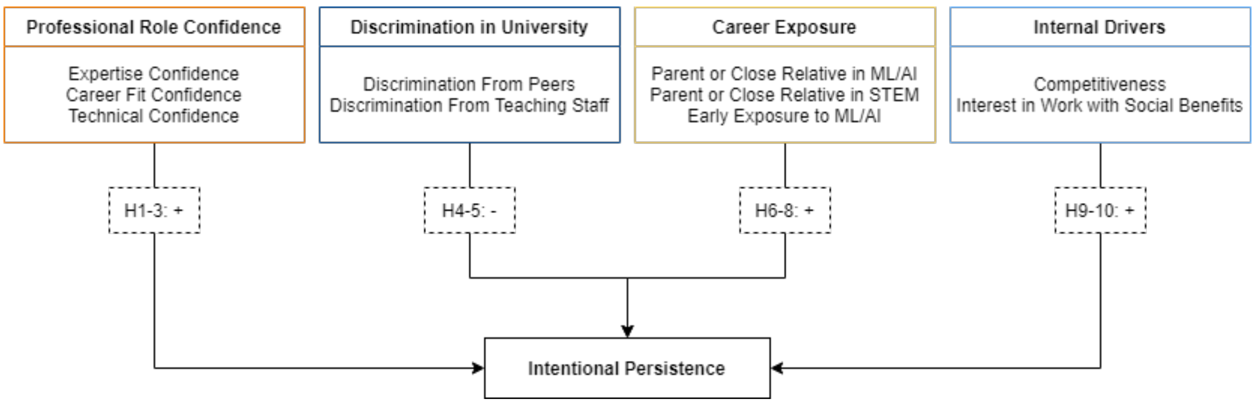

Figure 1: Graphical Representation of the Predictors of Intentional Persistence

Data and Methods

Data

The stated hypotheses were analyzed through original panel data. We sampled 279 students at the University of Toronto - a major Canadian university that facilitates extensive educational programming in ML/AI. This includes undergraduate and graduate engineering students. Students in ML/AI courses that were offered as part of an official ML/AI academic specialization were invited to participate in the survey. The study was reviewed and approved by the University Ethics Review Office. Data was collected through paper surveys distributed in classes. The survey was open to students in any year of study but mostly students in Year 3 – 4 and in their graduate studies as they represent those who were enrolled in the ML/AI specialization courses. Several engineering divisions/departments were represented among survey respondents. Departments closely associated with ML/AI education, such as the Department of Electrical and Computer Engineering and the Division of Engineering Science represent 72% of survey respondents. Departments that are more loosely associated with ML/AI education, such as the Department of Mechanical and Industrial Engineering, the Department of Chemical Engineering, and the Department of Civil and Mineral Engineering represent the remaining 28% of survey respondents. The gender distribution of survey respondents deviated from the reported values of representation in the AI industry [39], with 38% identifying as women and 61% identifying as men. These numbers closely mirror the University of Toronto Faculty of Applied Science and Engineering student population which was reported in 2019 to be composed of 35% women across all years of study [41]. It may be interesting to note here that through contacting the teaching staff of ML/AI courses for survey distribution coordination, it was observed that 100% of the professors and teaching assistants of the sampled courses were men.

Dependent Variables

The two dependent variables are the Intentional Persistence in engineering and in ML/AI. The Intentional Persistence in engineering is measured through a similar method described by Cech et al. [15] wherein the respondents indicate the likelihood they will “be an ML/AI engineer in five years” (1 = very unlikely to 5 = very likely). The Intentional Persistence in ML/AI is measured through the response to the prompt “As a result of my ML/AI education, I will advance to the next level in a machine learning career” (1 = very unlikely to 5 = very likely).

Independent Variables

The measure of Professional Role Confidence including Expertise Confidence and Career Fit Confidence was modeled on the work by Cech et al. [15]. Professional Role Confidence was assessed based on an undergraduate coursework exposure to ML/AI engineering that included exposures ranging from one course to the last course of a multi-course specialization. Each survey question assessing Professional Role Confidence asks respondents to frame their answer within the context of their ML/AI courses. The Expertise Confidence (alpha = 0.66) measure is a combination of the Likert-scale rated confidence in three areas (where 1 = strongly disagree to 5 = strongly agree). The two respective survey questions are “As a result of my ML/AI education, I have developed useful skills” and “As a result of my machine learning courses, I will have the ability to be successful in my career.” The Career Fit Confidence (alpha = 0.62) measure is a combination of the Likert-scale rated confidence in the following three areas: “A career in ML/AI is the right profession for me,” “I will have a satisfying job,” and “I am committed to machine learning, compared to my classmates.”

The new measure of Technical Confidence (alpha = 0.68) asks the respondents to rate their current skill level on the Likert scale (where 1 = lowest 10% and 5 = highest 10 %) in “understanding of the material taught in ML/AI classes,” “computer programming skills,” and “math and statistics skills,” each relative to their peers.

The other determinants of Intentional Persistence were measured through specifically constructed survey questions. Competitiveness, peer discrimination, teaching staff discrimination and interest in work with social benefits were reported on a Likert scale (where 1 = strongly disagree to 5 = strongly agree) as a response to the prompts “I consider myself a competitive person,” “I have experienced discrimination from my peers in my university courses,” “I have experienced discrimination from the teaching staff in my university courses,” and “I am interested in engaging in work with social benefits.”

To evaluate the effect of having a parent or close relative in a related field, participants responded “yes” or “no” to the statements “I have a parent or close relative in a field related to Machine Learning / Artificial Intelligence” and “I have a parent or close relative in a field related to STEM.” Exposure to a potential career in ML/AI was measured by the question “When were you exposed to a potential career in Machine Learning?” and grouped into four categories: “Elementary school or younger,” “Middle School,” “High School,” and “University.” Finally, respondents were asked “What made you decide to pursue a specialization in ML/AI?” in an open text form to encourage unique responses.

Data Analysis

An ordinal logistic regression model was used to evaluate the factors that were hypothesized to predict Intentional Persistence in engineering and ML/AI. The T-test was used for the hypothesis test for ordinal variables and the Chi-squared test was used for the hypothesis test for binary variables. These values indicate the significance of the difference between men and women.

Results and Discussion

Table 1 summarizes the mean and standard deviation of all of the measured independent and dependent variables. We did not find evidence to reject the null hypothesis – that there is no difference between men and women in the Intentional Persistence, Expertise Confidence and Career Fit Confidence, and thus the data does not confirm Hypotheses 1b and 2b. The one Professional Role Confidence measure, the new measure of Technical Confidence is shown to be significantly higher in men than women (p-value <0.05), which is consistent with Hypothesis 3b. The experienced discrimination from peers was significantly greater for women than men (p-values <0.05), which is consistent with Hypothesis 4b. There was no statistically significant difference between men and women found for discrimination from teaching staff, Career Exposure variables (Parent in ML/AI, Parent in STEM, Early Exposure) or Internal Driver variable (Interest in Work with Social Benefits, Competitiveness). This is inconsistent with Hypotheses 5b, 6b, 7b, 8b, 9b, and 10b.

The self-reported Grade Point Average (GPA) of men and women was not found to be significantly different. However, it should be noted that only 59% of respondents reported their GPA. This objective measure of academic performance was originally intended to serve as a ground truth but will not be further used in the analysis of these results as it was under-reported and self-reported, and it may incorporate personal bias.

The remaining hypotheses were tested using the ordinal logistic regression models whose coefficients are shown in Table 2. The significance of each coefficient is reported in the same table. Two models are shown in each of the tables. Model 0 includes only control variables. Model 1 includes all controls and predictor variables. Performing the ordinal logistic regression of Model 1 separately for women and men showed that several coefficients significantly differed between the two datasets. For predicting the Intentional Persistence in Engineering, being Chinese or Other Visible Minority is a positive predictor for women and a negative predictor for men. Discrimination from Teaching Staff is a negative predictor for women and a positive predictor for men. In Model 2I, three interactions terms between women and Chinese, other Visible Minority, and Discrimination from Teaching Staff are therefore included. For predicting the Intentional Persistence in ML/AI, the Chinese and Other Visible Minority variables are similarly significantly different between men and women. However, competitiveness is a negative predictor for Intentional Persistence in ML/AI for women and a positive predictor for men. These three interaction terms are included in Model 2II.

Table 1. Mean and Standard Deviation of Independent and Dependent Variables and the Significance of the Difference Between Men and Women. Other Visible Minorities includes respondents who self-identified as Filipino, Latin American, Arab, West Asian, and Japanese.

	All		*Women (n=105)*		*Men (n = 169)*		*T-test/Chi^2 test significance*
	Mean	SD	Mean	SD	Mean	SD	
Percent women	0.38						
Percent Aboriginal person	0.00						
Chinese	0.51		0.54		0.49		
South Asian	0.13		0.10		0.15		
Black	0.02		0.01		0.02		
Other Visible Minorities	0.18		0.2		0.18		
Percent 1st Year	0.00		0.01		0.00		
Percent 2nd Year	0.00		0.01		0.00		
Percent 3rd Year	0.53		0.57		0.52		
Percent Internship Year	0.02		0.03		0.01		
Percent 4th Year	0.34		0.31		0.36		
Percent Graduate Studies	0.10		0.07		0.11		
Intentional Persistence	3.91	1.22	3.85	1.25	3.96	1.19	
Expertise Confidence	3.54	0.95	3.52	0.88	3.55	1.03	
Career Fit Confidence	3.27	1.03	3.19	1.00	3.30	1.05	
Technical Confidence	3.36	0.90	3.24	0.83	3.43	0.92	**
GPA	3.49	0.57	3.41	0.48	3.55	0.54	
Discrimination from Peers	1.70	0.93	1.84	0.94	1.60	0.88	*
Discrimination from Teaching Staff	1.53	0.83	1.56	0.89	1.50	0.83	
Percent Parent in ML/AI	0.08		0.07		0.08		
Parent in STEM	0.53		0.63		0.48		
Elementary school or younger	0.01		0.01		0.01		
Middle school	0.00		0.01		0.00		
High school	0.11		0.07		0.14		
University	0.87		0.91		0.84		
Social Benefit Interest	3.72	1.02	3.83	0.90	3.67	1.06	
Competitiveness Score	3.57	1.09	3.52	1.12	3.60	1.05	

**p < .05; **p < .01; ***p < .001 (two-tailed test).*

One striking difference between the coefficients for the women-only model and the men-only model are those pertaining to the Discrimination from Teaching Staff. That variable is a significant negative predictor for Intentional Persistence in Engineering for women and has a very small coefficient for men, indicating little predictive power. However, discrimination from peers is not a negative predictor in any case for Intentional Persistence in Engineering, which is inconsistent with Hypothesis 4a.

Career Fit Confidence is a significantly positive predictor of Intentional Persistence in ML/AI and Engineering, which is consistent with Hypothesis 2a. Technical Confidence is not a predictor of Intentional Persistence, which is inconsistent with Hypothesis 3a. Expertise Confidence is only a predictor of Intentional Persistence in ML/AI and not in Engineering, which is inconsistent with the first part of Hypothesis 1a and consistent with the second. Social Benefit Interest is a positive predictor of Intentional Persistence in engineering and is a negative predictor in ML/AI. This both contradicts and supports Hypothesis 9a. This is an unexpected result as all predictors were hypothesized to predict Intentional Persistence in engineering and ML/AI in the same direction. In this case, it predicts them in the opposite direction.

Table 2: Coefficients of the Ordinal Logistic Regression Predicting Intentional Persistence in Engineering and in ML/AI. The first column (I) in each model corresponds to Intentional Persistence in engineering. The second column (II) in each model corresponds to Intentional Persistence in ML/AI.

	Model 0		*Model 1*		*Model 1 - Woman*		*Model 1 - Man*		*Model 2*	
	I	II	I	II	I	II	I	II	I	II
Woman	-0.148	-0.230	-0.248	-0.280					-0.982	4.660***
Technical Confidence			0.155	0.036	0.515	-0.178	-0.005	0.137	0.177	0.018
Expertise Confidence			-0.038	1.937***	-0.205	2.582***	0.141	1.989***	-0.038	2.148***
Career Fit Confidence			0.486*	0.949***	0.534	0.531	0.373	1.024***	0.450*	0.866***
Discrimination From Peers			0.335†	0.063	0.521†	-0.291	0.101	0.465	0.223	0.115
Discrimination From Teaching Staff			-0.363†	0.007	-0.703*	0.222	0.040	-0.345	-0.029	-0.023
Parent in ML/AI			0.088	-0.194	-0.521	-1.242	0.253	0.278	0.031	-0.280
Parent In STEM			0.148	0.311	0.096	0.680	0.078	0.303	0.084	0.418
Early Exposure			-0.342	0.216	0.264	1.211	-0.586	-0.012	-0.405	0.235
Social Benefit Interest			0.279*	-0.196	0.385	-0.257	0.317*	-0.245	0.312**	-0.262*
Competitiveness			-0.140	-0.010	-0.384†	-0.511*	0.075	0.326†	-0.106	0.419*
Woman x Chinese									1.659*	-2.083*
Woman x Other Minorities									1.948*	-1.717*
Woman x Discrimination From Teaching Staff									-0.542†	
Women x Competitiveness										-0.924***
AI Certificate	-0.055	0.589	0.235	0.679	1.152	0.937	-0.287	0.677	0.148	0.872†
Minor in Artificial Intelligence Engineering	-0.082	1.024**	-0.108	0.571	0.182	0.731	-0.280	0.648	-0.214	0.763*
Machine Intelligence Option	-0.172	1.145**	-0.263	0.140	0.635	0.957	-0.456	-0.083	-0.188	0.422
Year4	-0.817**	-0.555†	-0.765*	-0.463	-0.499	-0.042	-0.808†	-0.207	-0.849**	-0.108
Graduate Studies	0.079	1.022*	-0.150	0.840	0.411	0.954	-0.262	1.300†	-0.284	1.361*
Chinese	0.106	-0.705*	0.211	-0.330	1.168	-1.616*	-0.365	0.432	-0.368	0.348
All Other Minorities	0.449	0.051	0.413	-0.105	1.654*	-1.178	-0.261	0.422	-0.249	0.344
Threshold 1	-2.805	-3.378	-0.340	4.782	1.099	1.463	-0.237	7.286	-0.536	7.007
Threshold 2	-2.102	-1.487	0.348	7.353	1.880	4.916	0.418	9.858	0.168	9.844
Threshold 3	-1.016	0.154	1.473	9.736	3.301	7.430	1.453	12.480	1.330	12.360
Threshold 4	0.174	2.243	2.749	12.925	4.392	11.525	2.945	15.478	2.635	15.632
Pseudo R-squared	0.052	0.160	0.113	0.551	0.212	0.561	0.132	0.621	0.143	0.584

*†p<0.1; *p < .05; **p < .01; ***p < .001*

Being a woman is a negative predictor of Intentional Persistence in engineering, which is consistent with the first part of Hypothesis 1c, but not in ML/AI, which is inconsistent with the second part of Hypothesis 1c. For women, being a Visible Minority is a significantly large positive predictor of Intentional Persistence in Engineering and a significant and large negative predictor in ML/AI. Being in the Graduate Studies level of education is a significant and large positive predictor of Intentional Persistence in ML/AI, but not in engineering.

Discussion

Control Variables

The percent of women in ML/AI engineering (38%) was found to be higher than both the reported number of women in the UofT Engineering program in undergraduate studies (35.4%) and in graduate studies (27.1%). This indicates that in the time between entering an engineering program and choosing to pursue a specialization, women may not be deterred from ML/AI at this institution. The reported percent of women in the ML/AI workforce (22%) is much lower than what was represented in this study. This could mean that there are factors that affect the representation of women in the workforce that are not captured in this study of the university environment. This could be compounded with the fact that the institution surveyed here has implemented initiatives to improve diversity that may not exist at other universities or in the workplace [41].

The percent of students identifying as a Chinese visible minority (51%) made up the majority of total respondents. All visible minorities represented 84% of all respondents. This is consistent with UofT's significant population of international students (41%). However, our measure of visible minority includes those who are domestic students who identify as a visible minority. Those domestic students account for the remaining visible minority students. This indicates that the student population has significant ethnic diversity which could be a contributing factor to the unique findings of this study.

Professional Role Confidence

Our results revealed differences from Cech's work [15] on Professional Role Confidence in men and women. Namely, we did not find evidence of a difference between the Expertise Confidence and Career Fit Confidence of men and women. Due to the independent nature of both studies, environmental factors such as the sociocultural differences between American and Canadian schools or population differences between engineering students and ML/AI engineering students could have affected this result.

The new measure of Technical Confidence is shown to be significantly higher in men than women which is consistent with Robinson's study of technical self-confidence [53]. Interestingly, this gap is not shown to translate into differences in other measures of Professional Role Confidence or Intentional Persistence in this study. However, this could become a factor outside of university, in the workplace [54].

Both Career Fit Confidence and Expertise Confidence are large positive predictors of Intentional Persistence in ML/AI. Career Fit Confidence is also a positive predictor of Intentional Persistence in engineering. Currently, the UofT Faculty of Applied Science and Engineering offers a 12 to 16-month internship year typically following the third year of study. As this professional experience may be a contributor to a student's Career Fit Confidence, further research into how successful this internship in fostering that Confidence should be conducted. More meaningful internship experiences offered earlier in a student's university education may also help to improve Career Fit Confidence of all students. Future research investigating the effects of timing and number of internship experiences on Career Fit Confidence could inform program planning that would increase persistence. The Expertise Confidence in ML/AI should be further fostered in the curriculum to increase persistence of students pursuing those specializations. Earlier explicit exposure to ML/AI specialization Expertise in their first two years of undergraduate studies may positively influence the Expertise Confidence and Intentional Persistence of students. Again, further investigation into the university exposure to ML/AI would be necessary.

Gender Discrimination

The experienced discrimination from peers was significantly greater in women than in men. It is important to note that this is prevalent even in educational institutions with higher than average representation of women in the student population. This indicates that simply increasing the percentage of women into the program is not effective in eliminating this discrimination. This is a serious finding that will require further research into the discrimination experienced by women in university and how to reduce its prevalence.

We found that experiencing discrimination from teaching staff was a significant negative predictor of Intentional Persistence for women in engineering. To increase persistence for women and ultimately, representation in the workforce, it is important to address discriminatory behaviour of the university teaching staff targeted at women. There should be efforts implemented immediately to eliminate this behaviour. Mandatory training of university teaching staff to identify and prevent discriminatory behaviour may be effective as a preliminary measure. Further research will be necessary to identify best practices of eliminating gender discrimination from university teaching staff.

Limitations & Future Work

Given time constraints, behavioural persistence was not measured. Similar analysis of the dependent variables listed in this study and behavioural persistence would elaborate on our understanding of the variables that predict the actual persistence of students in the field of ML/AI. This would likely involve contacting the survey respondents in 5 years to assess their actual chosen career path. This study was confined to the student population of the University of Toronto. Further studies of students at different universities with ML/AI specializations could add to the findings discussed in this study.

Some findings that are noted in the results have not been extensively discussed such as competitiveness being a positive predictor for Intentional Persistence in men but a negative predictor for women and the Visible Minority factor being a positive predictor for women in engineering but not in ML/AI. These findings are not directly captured by the hypotheses or their associated rationale outlined at the beginning of the study. Therefore, future work to understand and further investigate these factors will be necessary.

Conclusions

The under-representation of women in ML/AI engineering is an emerging issue that parallels challenges faced in engineering more broadly. The Intentional Persistence, reported by upper-year undergraduate and graduate students in this study, has implications for the future representation on women in the ML/AI workforce. There are many factors that can affect this Intentional Persistence in ML/AI and engineering, and several predictors have been identified in this study:

- Expertise Confidence is a positive predictor for Intentional Persistence in ML/AI
- Career Fit Confidence is a positive predictor for Intentional Persistence in ML/AI and Engineering
- Discrimination from Teaching Staff is a negative predictor for the Intentional Persistence of women in engineering.

These findings highlight specific areas for improvement within the university education system. Efforts to foster Expertise Confidence and Career Fit Confidence while eliminating gender discrimination perpetrated by the Teaching Staff, could increase the levels of persistence in women students, ultimately leading to more women in the workforce.

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References

[1] M. I. Jordan and T. M. Mitchell, *Machine learning: Trends, perspectives, and prospects,* vol. 349, American Association for the Advancement of Science, 2015, pp. 255-260.

[2] J. Zou and L. Schiebinger, *Design AI so that its fair,* vol. 559, Nature Publishing Group, 2018, pp. 324-326, 2016.

[3] "AI and bias - IBM Research - US," [Online]. Available: https://www.research.ibm.com/5-in-5/ai-and-bias/.

[4] J. Buolamwini, "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification" 2018.

[5] O. Ali OmarAli, T. De Bie, N. Mosdell, J. Lewis and N. Cristianini, "Automating News Content Analysis: An Application to Gender Bias and Readability," 2010.

[6] D. Citron and F. Pasquale, "The Scored Society: Due Process for Automated Predictions," *Faculty Scholarship,* 1 1 2014.

[7] T. Bolukbasi, K.-W. Chang, J. Zou, V. Saligrama and A. Kalai, "Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings," in *Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings*, 2016.

[8] S. Leavy, "Gender bias in artificial intelligence: The need for diversity and gender theory in machine learning," in *Proceedings - International Conference on Software Engineering*, 2018.

[9] "Global Gender Gap Report 2018 - Reports - World Economic Forum," [Online]. Available: https://reports.weforum.org/global-gender-gap-report-2018/assessing-gender-gaps-in-artificial-intelligence/#view/fn-21.

[10] L. M. Shore, B. G. Chung-Herrera, M. A. Dean, K. H. Ehrhart, D. I. Jung, A. E. Randel and G. Singh, "Diversity in organizations: Where are we now and where are we going?," *Human Resource Management Review,* vol. 19, no. 2, pp. 117-133, 6 2009.

[11] V. Hunt, D. Layton and S. Prince J A N U A, "Why diversity matters," 2015.

[12] E. A. Deitch, A. Barsky, R. M. Butz, S. Chan, A. P. Brief and J. C. Bradley, "Subtle Yet Significant: The Existence and Impact of Everyday Racial Discrimination in the Workplace," *Human Relations,* vol. 56, no. 11, pp. 1299-1324, 22 11 2003.

[13] C. Hill, C. Corbett and A. St. Rose, Why so few? : women in science, technology, engineering, and mathematics, AAUW, 2010, p. 109.

[14] S. Hoffmann and H. H. Friedman, "MACHINE LEARNING AND MEANINGFUL CAREERS: INCREASING THE NUMBER OF WOMEN IN STEM," *Journal of Research in Gender Studies,* pp. 11-27, 2018.

[15] E. Cech, B. Rubineau, S. Silbey and C. Seron, "Professional role confidence and gendered persistence in engineering," *American Sociological Review,* vol. 76, no. 5, pp. 641-666, 10 2011.

[16] J. N. Magarian and A. Olechowski, "Engineering Students and Group Membership: Patterns of Variation in Lead-ership Confidence and Risk Orientation Engineering Students and Group Membership: Patterns of Variation in Leadership Confidence and Risk Orientation".

[17] D. C. Blanch, J. A. Hall, D. L. Roter and R. M. Frankel, "Medical student gender and issues of confidence," *Patient Education and Counseling,* vol. 72, no. 3, pp. 374-381, 9 2008.

[18] J. Butter, T. H. Grant, M. Egan, M. Kaye, D. B. Wayne, V. Carrión-Carire and W. C. McGaghie, "Does ultrasound training boost Year 1 medical student competence and confidence when learning abdominal examination?," *Medical Education,* vol. 41, no. 9, pp. 843-848, 9 2007.

[19] W. J. Hughes, "PERCEIVED GENDER INTERACTION AND COURSE CONFIDENCE AMONG UNDERGRADUATE SCIENCE, MATHEMATICS, AND TECHNOLOGY MAJORS," *Journal of Women and Minorities in Science and Engineering,* vol. 6, no. 2, p. 14, 2000.

[20] J. Colyar and B. S. Woodward, "Women Students' Confidence in Information Technology Content Areas," *Information Systems Education Journal,* vol. 6, 2008.

[21] M. Sobel, J. Gilmartin and P. Sankar, "Class Size and Confidence Levels among Female STEM Students [Impact]," *IEEE Technology and Society Magazine,* vol. 35, no. 1, pp. 23-26, 2016.

[22] D. I. Hanauer, M. J. Graham and G. F. Hatfull, "A Measure of College Student Persistence in the Sciences (PITS)," *CBE—Life Sciences Education,* vol. 15, no. 4, p. ar54, 12 2016.

[23] B. F. French, J. C. Immekus and W. C. Oakes, "An Examination of Indicators of Engineering Students' Success and Persistence," *Journal of Engineering Education,* vol. 94, no. 4, pp. 419-425, 10 2005.

[24] P. D. A. Gardner, *Pursuing an Engineering Degree: An Examination of Issues Pertaining to Persistence in Engineering.,* Collegiate Employment Research Institute, Michigan State University, 113 Student Services, East Lansing, MI 48824 ($5.00)., 1990.

[25] S. Makridakis, *The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms,* vol. 90, Elsevier Ltd, 2017, pp. 46-60.

[26] H. J. Wilson, P. R. Daugherty and N. Morini-Bianzino, "The Jobs That Artificial Intelligence Will Create", *MITSloan Management Review*, vol. 58, no. 4, pp. 14-16, 2017.

[27] A. Parker and K. Marcynuk, "THE SELF-REPORTED CONFIDENCE AND PROFICIENCY LEVELS OF UNDERGRADUATE ENGINEERING STUDENTS IN AN ENGINEERING TECHNICAL COMMUNICATION COURSE," *Proceedings of the Canadian Engineering Education Association (CEEA),* 7 8 2015.

[28] A. Parker, K. Marcynuk and V. Scholar, "The Self-Reported Confidence and Proficiency Levels in Communication Skills: A Comparison of Senior Capstone Students and Undergraduate Students in a Technical Communication Course," *Proceedings of the Canadian Engineering Education Association (CEEA),* 2 12 2018.

[29] M. C. Paretti, "Communication as Professional Practice: Designing Assignments to Develop Engineering Professionals," 2005.

[30] S. E. Peyre, C. G. Peyre, M. E. Sullivan and S. Towfigh, "A Surgical Skills Elective Can Improve Student Confidence Prior to Internship," *Journal of Surgical Research,* vol. 133, no. 1, pp. 11-15, 6 2006.

[31] C. M. Tetta, "AI: What's in it for you? Career pointers that may lead the intelligent to artificial intelligence," *IEEE Potentials,* vol. 5, no. 3, pp. 19-21, 3 5 2013.

[32] "Prerequisites and Prework | Machine Learning Crash Course," [Online]. Available: https://developers.google.com/machine-learning/crash-course/prereqs-and-prework.

[33] D. Chachra and D. Kilgore, "Exploring Gender and Self-confidence in Engineering Students: A Multi-method Approach," *ASEE Annual Conference and Exposition, Conference Proceedings*, 2009.

[34] L. Irani, "Understanding Gender and Confidence in CS Course Culture," 2004.

[35] E. Seymour, "The loss of women from science, mathematics, and engineering undergraduate majors: An explanatory account," *Science Education,* vol. 79, no. 4, pp. 437-473, 7 1995.

[36] J. W. Graham and S. A. Smith, "Gender differences in employment and earnings in science and engineering in the US," *Economics of Education Review,* vol. 24, no. 3, pp. 341-354, 6 2005.

[37] L. Mccullough, "Women's Leadership in Science, Technology, Engineering & Mathematics: Barriers to Participation," 2011.

[38] T. Conefrey, "Sexual Discrimination and Women's Retention Rates in Science and Engineering Programs," 2001.

[39] "Women and Men in STEM Often at Odds Over Workplace Equity | Pew Research Center," [Online]. Available: https://www.pewsocialtrends.org/2018/01/09/women-and-men-in-stem-often-at-odds-over-workplace-equity/.

[40] "Women in Engineering: A Review of the 2018 Literature - All Together," [Online]. Available: https://alltogether.swe.org/2019/04/women-in-engineering-a-review-of-the-2018-literature/.

[41] "Annual Report 2019," *University of Toronto Faculty of Applied Science and Engineering*, Toronto, 2019. [Online]. Available: https://www.engineering.utoronto.ca/files/2019/09/UTENG_Annual_Report_2019_Web_CH10_Diversity-2.pdf.

[42] M. de Philippis, "STEM Graduates and Secondary School Curriculum: Does Early Exposure to Science Matter?," *SSRN Electronic Journal,* 28 6 2017.

[43] K. Holmes, J. Gore, M. Smith and A. Lloyd, "An Integrated Analysis of School Students' Aspirations for STEM Careers: Which Student and School Factors Are Most Predictive?,"

International Journal of Science and Mathematics Education, vol. 16, no. 4, pp. 655-675, 1 4 2018.

[44] M. Mcpherson, L. Smith-Lovin and J. M. Cook, "BIRDS OF A FEATHER: Homophily in Social Networks," 2001.

[45] W.-C. Mau, M. Domnick and R. A. Ellsworth, "Characteristics of Female Students Who Aspire to Science and Engineering or Homemaking Occupations," *The Career Development Quarterly,* vol. 43, no. 4, pp. 323-337, 6 1995.

[46] M. Chui, M. Harryson, J. Manyika, R. Roberts, R. Chung, A. van Heteren and P. Nel, "NOTES FROM THE AI FRONTIER APPLYING AI FOR SOCIAL GOOD," 2018.

[47] T. W. Nattkemper, B. Arnrich, O. Lichte, W. Timm, A. Degenhard, L. Pointon, C. Hayes and M. O. Leach, "Evaluation of radiological features for breast tumour classification in clinical screening with machine learning methods," *Artificial Intelligence in Medicine,* vol. 34, no. 2, pp. 129-139, 6 2005.

[48] D. Setó-Pamies, "The Relationship between Women Directors and Corporate Social Responsibility," *Corporate Social Responsibility and Environmental Management,* vol. 22, no. 6, pp. 334-345, 11 2015.

[49] S. L. Eddy, S. E. Brownell and M. P. Wenderoth, "Gender gaps in achievement and participation inmultiple introductory biology classrooms," *CBE Life Sciences Education,* vol. 13, no. 3, pp. 478-492, 2 9 2014.

[50] N. C. Chesler, G. Barabino, S. N. Bhatia and R. Richards-Kortum, "The pipeline still leaks and more than you think: A status report on gender diversity in biomedical engineering," *Annals of Biomedical Engineering,* vol. 38, no. 5, pp. 1928-1935, 5 2010.

[51] M. Attaran and P. Deb, "Machine Learning: The New 'Big Thing' for Competitive Advantage," *International Journal of Knowledge Engineering and Data Mining,* vol. 5, no. 1, p. 1, 2018.

[52] R. Perrault, Y. Shoham, E. Brynjolfsson, J. Clark, J. Etchemendy, B. Grosz Harvard, T. Lyons, J. Manyika, J. Carlos Niebles and S. Mishra, "Artificial Intelligence Index Report 2019," Stanford, 2019.

[53] J. G. Robinson and J. S. McIlwee, "Women in Engineering: A Promise Unfulfilled?," *Social Problems,* vol. 36, no. 5, pp. 455-472, 12 1989.

[54] P. Sageev and C. J. Romanowski, "A Message from Recent Engineering Graduates in the Workplace: Results of a Survey on Technical Communication Skills," *Journal of Engineering Education,* vol. 90, no. 4, pp. 685-693, 10 2001.