ASEE 2022 ANNUAL CONFERENCE
Excellence Through Diversity
MINNEAPOLIS, MINNESOTA, JUNE 26TH-29TH, 2022 ASEE

Paper ID #37191

A Longitudinal Analysis of Pathways to Computing Careers: Defining Broadening Participation in Computing (BPC) Success with a Rearview Lens

Mercy Jaiyeola

An Assistant Professor of Computer Science in the Department of Mathematics and Computer Science at Hampden-Sydney College

Sarah B Lee (Director & Professor)

Sarah Lee serves as Professor and Director of the School of Computing Sciences and Computer Engineering at The University of Southern Mississippi. Following a 19-year career at FedEx Corporation and since entering academia in 2011, Sarah has created programs to encourage persons historically marginalized in computing to enter computing education pathways. Sarah holds a BS in Computer Information Systems from the Mississippi University for Women and a master's degree in computer science (CS) from Mississippi State, and a PhD in CS from the University of Memphis.

A Longitudinal Analysis of Pathways to Computing Careers: Defining Broadening Participation in Computing (BPC) Success with a Rearview Lens

Mercy O. Jaiyeola, Sarah B. Lee, Shahram Rahimi, Allen Parrish, Michael Taquino
Hampden-Sydney College/University of Southern Mississippi/Mississippi State University/University of Alabama/Mississippi State University

Abstract

Efforts to increase the participation of groups historically underrepresented in computing studies, and in the computing workforce, are well documented. It is a national effort with funding from a variety of sources being allocated to research in broadening participation in computing (BPC), but as existing literature shows, the growth in representation of traditionally underrepresented minorities is not commensurate to the efforts and resources that have been directed toward this goal. This paper tackles the underrepresentation problem by identifying what has worked (leveraging existing real-world data) to increase representation. This work studies the educational pathways of persons who have successfully transitioned into the computing workforce and identifies the common roadmaps that have contributed to retention, persistence, and success in attaining computing employment. Descriptive statistics, logistic regression, and predictive analytics were employed to identify educational pathways that have resulted in successful employment outcomes for women and blacks in computing.

Keywords

Longitudinal analysis, Computing educational pathways, Computing employment outcomes, Underrepresented minorities, broadening participation in computing

Introduction

There is an abundance of open computing jobs in the United States of America (USA), but the rate of supply of computing professionals to the computing workforce has lagged behind the level of demand for these talents[1-3].

This research studies this gap, particularly along the racial and gender dimensions, and seeks a different perspective for understanding the underrepresentation problem in computing than what has been seen in the existing literature. This research illustrates a roadmap of how current computing professionals have reached their employment outcomes and maps this knowledge to distinguishing characteristics of those professionals such as gender, race, and educational preparation.

Efforts to increase the participation of groups historically underrepresented in computing studies, and in the computing workforce, are well documented. It is a national effort with funding from a variety of sources being allocated to research in broadening participation in computing (BPC). Many of the BPC efforts are funded by the National Science Foundation (NSF)[3-5] but as existing literature shows, the growth in representation of traditionally underrepresented minorities and women is not commensurate to the efforts and resources that have been directed toward this aim[6-7].

Thus, this research brings a different perspective to understanding and addressing the underrepresentation problem in computing. Many of the BPC efforts that are evident in the literature have identified one or more barriers that have impeded the representation of the underrepresented minorities and have attempted to tackle these individual barriers. Instead of attempting to tackle the barriers (what does not work), this research tackles the underrepresentation problem by identifying what has worked (leveraging existing real-world data) to increase representation. To achieve that, this work studies the educational pathways of persons who have successfully transitioned into the computing workforce and identifies the common roadmaps that have contributed to retention, persistence, and success in attaining computing employment. This strategy is impactful because the identification of factors that increase representation across racial and gender dimensions will inform the direction of future investments in BPC efforts.

In pursuit of this goal, the following research questions are addressed:

1. What are the common themes across educational pathway experiences that emerge from the analysis of computing professionals' data across racial and gender dimensions?

2. Which of these common experiences result in successful long-term (greater than 3 years) employment outcomes in the technology sector for women and blacks?

3. How do the findings of this study inform national investment in broadening participation efforts that seek to increase racial and gender diversity in the computing workforce?

This research studies the computing education and workforce landscape within the United States of America with specific focus on the outcomes of computing studies and employment in the Southern region of the USA.

Literature review

Composition of the Computing Field

According to Computing Curricula 2005[8], the computing field includes these five disciplines: Computer Engineering (CE), Computer Science (CS), Information Systems (IS), Information Technology (IT), and Software Engineering (SE). As seen in Computing Curricula 2020[9], newer computing disciplines such as Artificial Intelligence and Data Science have been added to the list of disciplines within the computing field. The computing field is a major area of focus in this research because as seen in Exter et al. (2018)[10], computing employment positions take longer to be filled than other types of professions. Also, in a news article[11] published by the Northeast Mississippi Daily Journal, a representative of a technology company said that in the state of Mississippi, "there are currently almost 1,000 unfilled job openings due to a shortage of qualified IT workers".

Employability and the concept of successful employment outcomes

According to the Commission on Higher Education and Employability[12], "Employability is a set of achievements —skills, understandings and personal attributes — that make graduates more likely to gain employment and be successful in their chosen occupations, benefiting themselves, the workforce, the community and the economy".

In the context of this research, the success of a person's employment outcome is dependent on about 5 factors:

1. Whether they were able to gain computing employment: Getting employed in a computing job is seen as a successful employment outcome whereas getting employed in a non-computing position is seen as an unsuccessful outcome, in the context of this research[13-14].

2. How soon they were able to gain their computing employment: After college, it takes the average graduate three to six months to get a job[15]. Within this research, a person who gets employed within a year of the completion of their educational program(s) is seen as successful whereas a person who gains their computing employment after a wait period of over one year is not as successful.

3. The rating of their company or employer: The higher a person's employer's rating is, the more successful their employment is assumed to be. For example, having work experience at a Fortune 500 company is usually perceived as a sign of success[16]. A computing employment at a Fortune500 company is seen as more successful than one at a Non-Fortune500 company.

4. Their salary level: An employee's salary level is usually reflective of the type of position they are employed in[13,14,17]. Within this research, a person with a low annual income (less than 50,000 USD) and a person with a medium annual income (between 50,000 and 100,000 USD) are seen as less successful than a person with a high annual income (greater than 100,000 USD).

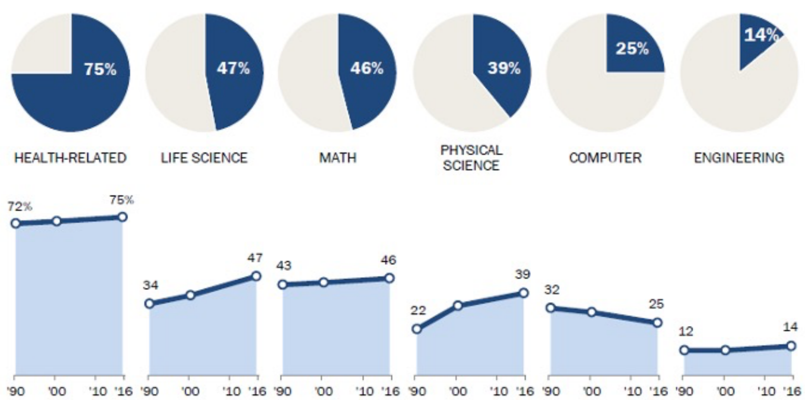
5. Whether they are able to persist in a computing field[13,18]: Within this research, an employee that is able to remain in the computing workforce for at least 3-5 years after they enter the workforce is seen as more successful than those who aren't able to persist for that long in those computing positions.

<u>Diversity in the STEM and computing workforce</u>

Over a decade ago, it was discovered that the ability of the United States (U.S.) to compete economically on a global scale is highly limited because of the US's inability to develop her science and engineering workforce. The STEM [science, technology, engineering, and mathematics] workforce is generally acknowledged to have a substantial effect on America's capacity to compete globally[6,19]. Hence, we see that the former U.S. President – Barack Obama – announced the "Computer Science for All" initiative in 2016 to build computing skills and computational thinking abilities in students, so that they can contribute to the digital economy[20]. President Barack Obama[21] also declared that increasing the diversity in the STEM workforce would make the USA more competitive.

The major demographic groups that have been identified as being underrepresented in the computing field (computing studies and computing workforce) are Women, Blacks, Hispanics, American Indians, and Alaska Natives[6,7,22]. It is important to diversify the computing workforce because women and the other racial minorities would contribute new innovation from their unique perspectives; their presence in the computing workforce would also be more reflective of the computing/technology user base than if they were excluded from the workforce[6]. These benefits, among others, would culminate in economic growth for the computing field and for the USA as a whole[1].

How has the computing workforce landscape looked like (in terms of its diversity) over the years? Even though there have been numerous efforts to increase diversity in the STEM workforce, there has not been a very significant difference in the STEM workplace demographics in spite of the increase in representation of women and racial minorities in the workplace. In 2018, women constituted 51% of the population and 46% of the civilian labor market in the United States[6]. However, they only made up 29% of the STEM workforce and 24% of the computing workforce[6-7]. According to the Pew Research Center[7], we see, in the figure below, that the representation of women in computing jobs has declined since 1990.



Despite their low representation, women in the STEM workforce have a higher representation than the racial minorities. While Whites made up about 70% of STEM workers in 2013, Hispanics, Blacks, and American Indians or Alaska Natives recorded a much lower participation in the STEM workforce. Hispanics made up about 6% of the STEM workforce. Comparably, Blacks made up about 9% of the STEM workforce. The American Indians or Alaska Natives made about 0.2% of STEM workers. Though the racial representation of underrepresented racial minorities is still very low, these statistics show that there has been an improvement from what obtained in 1990 when STEM workers were 83% white, 4% Hispanic, and 7% black[6-7]

Barriers to representation of women and other racial minorities

Researchers have discovered several factors that contribute to the underrepresentation of these minority groups. Google & Gallup (2016)[22] found that only about 11% of women and 16% of Hispanics claim to have seen people like them "doing CS" on TV shows. Seeing people like them doing CS inspires underrepresented minorities to desire to achieve similar goals, but the statistics show that women and Hispanics have a very low percentage of exposure to role models and positive external influences. Female students are less confident (48% vs. 65%) in their ability to learn CS than male students are[22]. There is not a high level of confidence from external sources either. Google & Gallup (2016)[22] reported that "Male students are more likely to be told by a parent or teacher that they would be good at CS (46% vs. 27% being told by a parent; 39% vs. 26% being told by a teacher)". Google & Gallup (2016)[22] also identified the perpetual social perception that CS is for certain groups of people: White or Asian males. In addition, CS is perceived as having little to no social relevance[2] which women seem to care more about.

Bridging the gender and racial gaps in the computing field

Seeing that the computing field is dominated by male, White, and Asian workers[2,6], a frequent strategy to fill up these vacant jobs is to recruit and attract traditionally underrepresented minorities into computing. According to research, attracting underrepresented minorities into computing studies would eventually result in the availability of a higher number of computing professionals for the workforce[1,2].

To achieve the aim of broadening participation in computing, many researchers have set out to study and provide strategies to overcome the barriers to representation of the underrepresented minorities in the computing field.

Efforts to broaden the participation of underrepresented minorities in computing include the Scalable Game Design project[23] targeted at middle school students to motivate their interest in computing and to develop their capacity for computational thinking. This project achieved a high level of participation of females and underrepresented minority students. EarSketch – a hybrid platform (included within a high school Computer Science Principles course) that combines computing with music[24], and the NSF-supported Mobile CS Principles (Mobile CSP) course are other strategies that target underrepresented minorities; all to broaden participation in CS[4].

Lamar University embarked on a program named INSPIRED (Increasing Student Participation In REsearch Development) to attract and retain women and other underrepresented minorities in CS. They employed the provision of peer support, mentors and role models, and the exposure of undergraduates to research and useful applications of CS[3]. In addition, the BRAID (Building, Recruiting, And Inclusion for Diversity) scheme is another strategy that has made a lot of difference in increasing representation of the traditionally underrepresented students[25].

Organizations such as the National Center for Women & Information Technology (NCWIT), the Association of Computing Machinery (ACM-W), Anita Borg Institute (ABI), Computing Research Association (CRA-W), Center for Minorities and People with Disabilities in Information Technology (CMD-IT), among others, have been established to increase the representation of women and minorities in computing studies and beyond, and they have recorded success thus far[25-26].

Apart from the immediate results on academic performance, recruitment, persistence across the computing pipeline, self-efficacy, etc., what is the impact of these schemes on the eventual employment outcome of the underrepresented minorities?

Many BPC efforts in the existing literature have designed and deployed solutions aimed at removing one or more barriers to representation, after which the impact (of the solution) on the representation of underrepresented minorities is evaluated. This is what this research describes as "looking forward". Using this strategy, several hypotheses are put forward and tested with the expectation that the employment gaps will be bridged. Unfortunately, under the "looking forward" strategy, the percentage of women in the STEM workforce has declined since 1990, and the percentage of racial minorities in the computing workforce has hardly broken into the double digits.

Contrary to the "looking forward" strategy, this research describes and tests the "rearview lens" strategy where the analysis begins with underrepresented individuals who have achieved successful employment outcomes. From this end point, this research works backwards to observe the pathways (educational decisions) that have resulted in those successes. Because the "rearview lens" strategy begins from a position of success, it is presented in this research as a strategy that promises to deliver a higher rate of success if the insight drawn from this strategy is used as a basis for future broadening participation efforts.

Methodology

In order to achieve the aim of this research, a longitudinal study of computing professionals who studied or worked (or are currently working) in Mississippi (and surrounding Southern states) was carried out. Their identification as computing professionals is based on the composition of the computing field as described in the literature review section. The educational and work history of these computing professionals was extracted from LinkedIn. The raw longitudinal data from LinkedIn consists of 303 rows and 77 columns, and it contains the educational and employment history of the data subjects. This dataset is available for review, on request. For every individual in the dataset, the following categorization was implemented:

Categorization of Educational History

- Each educational experience was categorized as a **computing** or **non-computing** degree.
- Each educational institution attended was also categorized as either a **R1**, **R2**, **D/PU**, **M1**, **M2**, **M3**, **BC**, **BAC**, **AC**, **SFI**, or **TC** institution, using the Carnegie classification.
- The Carnegie classifications were carried out using the lists found on Carnegie Basic Classification Description and Carnegie Classification of Institutions of Higher Education

Categorization of Employment History

- For each employment experience, the Employment Status variable was created with possible attributes: **Employed**, **Unemployed**, or **Self-employed**.
- Each employment experience was categorized as either **Computing** or **non-computing**, under the Employment Type variable**.** This categorization was done, based on what the composition of the computing field as described in the literature review section and the existing literature[27-28] characterizes as a computing job.

- For each employment experience, the employer was categorized as either a **Fortune 500** or **Non-Fortune500** company, under the Employer Rank variable, according to the 2020 list of Fortune 500 companies[29].

- For each employment experience, the average annual salary was calculated[30-32]. This average salary was then categorized as either **Low** (less than $50,000), **Medium** ($50,000 to $100,000), or **High** (greater than $100,000), under the Salary Level variable.

Description of Final Dataset for Analysis

The resulting dataset, after categorization, was further processed, resulting in a dataset containing 301 rows and 13 columns. The final 13 variables in the dataset are described as follows:

Race, **Gender**, **Highest Degree Attained** (HSL (High School or Less), SC (Some College), and BDH (Bachelor's Degree or Higher)), **Traditional Degree** (degree ranging from an Associate's degree to a Doctoral degree), **Alternative Degree** (Certifications, coding bootcamp degrees, and other degree), **Computing Degree**, **Highest Institution Ranking** (The rank of the highest-ranking institution attended), **Internship**, **Current Employment status**, **Time Elapsed before computing job** (NW (No Wait), MW (Moderate Wait), and LW (Long Wait)), **Persistence in Computing field**, **Highest Computing Employer Ranking** (Rank of the highest-ranking employer), and **Highest Computing Salary Level** (Highest salary level in the computing employment history of the data respondent).

Given this data, the pathways of the data subjects were studied especially along the race and gender lines, in order to answer the research questions listed in the introduction section.

Data Analysis with Stata

The 13 variables listed in the section above were dichotomized and coded into dummy variables in Stata. Of the 13 variables, the independent variables were made up of the first 8 variables made up. 0 was assigned to the less desirable attribute (reference group) and 1 assigned to the more desirable attribute (target group) of each of these independent variables. Of the 13 variables, the dependent variable was arrived at by pre-processing the last 5 variables in the final dataset in a similar manner as the independent variables. 0 was assigned to the less desirable attribute and 1 was assigned to the more desirable attribute.

These five variables were converted into a “Success Index” which is the sum of the dummy values that were assigned to the five variables above. The Success Index holds a value between 0 and 5, where 0 represents a very unsuccessful computing employment outcome and 5 represents a very successful computing employment outcome. the Success Index is converted to a new categorical variable (Employment Outcome) with two attributes: Unsuccessful and Successful. Success Index values of 1 – 3 are represented by the “Unsuccessful” attribute of the “Employment Outcome” variable, while the Success Index values of 4 and 5 are assigned to the “Successful” attribute of the “Employment Outcome” variable. The “Successful” attribute of this variable is coded as 1 and the “Unsuccessful” attribute is coded as 0.

The "Employment Outcome" variable is the dependent variable for the data analysis.

The final pre-processed data (in Stata) is made up of 194 records (rows) and 13 variables (columns) after the exclusion of missing data and the generation of a common data sample. Below is the descriptive statistics table for the pre-processed data:

Variable	Number of Observations	Mean	Standard Deviation	Min Value	Max Value
Independent Variables					
Race	194	0.180	0.386	0	1
Gender	194	0.180	0.377	0	1
Bachelors' Degree and Higher	194	0.938	0.242	0	1
Some College	194	0.052	0.222	0	1
Traditional degree	194	0.990	0.101	0	1
Alternative degree	194	0.392	0.489	0	1
Computing degree	194	0.995	0.072	0	1
Rank1	194	0.758	0.430	0	1
Rank3	194	0.041	0.199	0	1
Internship	194	0.242	0.430	0	1
Dependent Variable					
Employment Outcome	194	0.722	0.449	0	1

This table shows that across racial lines, about 18% of the data respondents are black while 82% are white; across gender lines, about 18% of the data respondents are female while the remaining 82% are male. The same follows for the remaining attributes.

Univariate Analysis in Stata

In order to answer the first research question as seen in the "Introduction" section, descriptive statistics are used. Univariate statistical analysis is employed to observe the various variables and to extract the current distribution of women and blacks across these variables.

Multivariate analysis with Logistic Regression and Predicted Probabilities

In order to answer the second research question as seen in the "Introduction" section, multivariate statistics (logistic regression and predicted probabilities) is used to measure the impact of the educational pathways of women and blacks on achieving successful employment outcomes. Logistic regression is used to predict the relationship between the independent (predictor) variables and dependent (target) variable. The resulting model is checked for multicollinearity. After an initial run of the logistic regression model, the independent variables: Computing Degree, Bachelors' Degree and Higher, and Some College are omitted from the model due to multicollinearity. The final logistic regression model consists of the following independent variables: Race, Gender, Traditional Degree, Alternative Degree, Rank1, Rank3, and Internship, with Employment Outcome as the dependent variable.

Predicted probabilities are employed to predict the target variable from any combination of the predictor (independent) variables, based on the results of the logistic regression model. Predicted probabilities are used, in this research, to describe the educational factors that result in a high probability of successful employment outcomes for women and blacks, and educational factors that have less probability of success.

Results/Discussion

Univariate Analysis Results

After examining several pairs of variables using two-way tables in Stata, here are the themes that are observed within the data: The education trends appear similar for both blacks and females: **possession of a traditional degree**, **attendance of a Rank1 institution**, **no internship**. Do these educational choices guarantee successful computing employment outcomes among females and blacks? Logistic regression and predicted probabilities were run on the dataset to show what educational choices are good predictors for successful employment outcomes.

Multivariate analysis with Logistic Regression Results

The logistic regression model was run in Stata. Here are the results of the regression:

Variables	B (Coefficient)	Standard Error	Odds Ratio	P
Race	-0.631	0.423	0.532	0.136
Gender	-0.366	0.448	0.694	0.415
Traditional Degree	1.665	1.521	5.288	0.274
Alternative Degree	0.938	0.378	2.556	0.013
Rank1	0.874	0.396	2.397	0.027
Rank3	1.171	0.975	3.225	0.230

Internship	0.555	0.420	1.742	0.186
Constant	-1.645	1.600	0.193	0.304
Pseudo R2	0.065			
Overall significance of model	0.0357			
Number of observations	197			

The Odds ratio measures the ratio of the odds (of predicting the dependent variable) for the variable attribute that is set to 1 (the group under observation), in relation to the odds of the variable attribute that is set to 0 (the reference group).

From our results, for instance, the odds are about 0.5 to 1 that a black person will have a successful computing employment outcome compared to non-blacks. Similarly, the odds are about 5 to 1 that an individual with a traditional degree will have a successful computing employment outcome compared to an individual without a traditional degree. Similarly, an individual who does an internship is almost 2 times more likely to achieve a successful computing employment than someone who does not do an internship.

The Coefficient measures the amount of change expected in the log-odds when there is a unit change in the independent variable, while all other variables remain unchanged. The coefficient also shows a similar relationship as the Odds ratio variable. A negative coefficient shows a lesser likelihood of the group under observation to achieve the target than the reference group. On the other hand, a positive coefficient indicates a higher likelihood of the group under observation to achieve the target than the reference group. Therefore, our regression table shows, for instance, that blacks are expected to have 0.631 fewer log-odds of achieving a successful employment outcome than non-blacks. Similarly, people with a traditional degree are expected to have 1.665 more log-odds of achieving successful employment outcome than those who do not possess a traditional degree.

The Standard error shows how much each variable’s coefficient differs from 0, measuring the statistical accuracy of the coefficient of each variable. The “Constant” variable represents the value of the dependent variable when all the independent variables are set to zero. In our table, when a white male does not possess a traditional degree or an alternative degree and does not attend either a Rank 1 or Rank 3 institution, and does not do an internship, he has odds of 0.2 to 1 of attaining a successful employment outcome.

As seen in the table, a total of 197 data points were analyzed. Pseudo R2 represents the relevance of the independent variables in this model to predicting the dependent variable. The pseudo R2 of 0.065 shows that 6.5% of obtaining a successful employment outcome is influenced (or can be predicted) by the independent variables used in this model. This shows that the pool of independent variables needs to be expanded. The overall regression model is statistically significant because its p-value equals 0.0357 which is less than 0.05. This means that the results of our overall model (that is, the ability of all the independent variables to predict the dependent variable) falls within a 95% confidence interval. On the other hand, only two of the independent variables – Alternative degree and Rank1 – possess statistical significance (when standing alone) with respect to their ability to predict the dependent variable.

Multivariate analysis with Predicted Probabilities Results

From the analysis results, there are a few combinations of independent variables that result in a high likelihood of employment success for blacks and women:

- Probability of success for a black person with an internship, a traditional degree, an alternative degree, and a Rank 3 institution education: **93.4%**
- Probability of success for a woman with an internship, a traditional degree, an alternative degree, and a Rank 3 institution education: **94.6%**

Based on this analysis, it is predicted that a **black** person who does an **internship**, possesses a **traditional degree**, possesses an **alternative degree**, and also attends a **Rank3 institution** has the **highest likelihood to obtain successful computing employment outcomes**. This also applies to **women**.

On the other hand, there are a few combinations of independent variables that result in a low likelihood of employment success for blacks and women:

- Probability of success for a black person with an internship, an alternative degree, and a Rank 1 institution education = **51.9%**
- Probability of success for a woman with an internship, an alternative degree, and a Rank 1 institution education = **57.2%**
- Probability of success for a black person with a traditional degree = **63.2%**
- Probability of success for a woman with a traditional degree = **68%**

A common pathway thread that results in the **least successful outcomes** for blacks and females include either attending only a **Rank 1 institution** or having only a **traditional degree**. Interestingly, this is the pathway that most women and black people have taken, as seen in the univariate analysis results section. This provides an explanation as to why women and blacks have not experienced a lot of successful computing employment outcomes.

Discussion

This research has shown that attending a Rank3 institution, that is, attending an associate-degree-granting college (e.g., community college) contributes to a successful employment outcome for women and blacks. This is in sharp contrast to the high probability of an unsuccessful employment outcome when women and blacks attend only a Rank1 institution. There could be a few reasons why this is the case. Research[33] shows that a sense of belonging is a predictor of success in college. Research[34] shows that first generation and underrepresented minority students (of which women and blacks are a part) who attend community colleges (a Rank3 institution) feel a stronger sense of belonging at these colleges, compared to their colleagues. It follows that a strong sense of belonging at community colleges would result in successful academic performance and successful employment outcomes.

There are many other factors that distinguish between the path that leads to successful employment outcomes versus the path that leads to unsuccessful employment outcomes for women and blacks. It might be helpful to consider factors like institution size or population, student-to-teacher ratio, teacher-as-mentor versus teacher-as-dictator model, whether the content taught is geared toward more theoretical knowledge or more practical knowledge, among other things. This is a possible area for future inquiry and research.

Given the data analysis results earlier shown, how can the extracted knowledge be of benefit to the broadening participation efforts in the computing field? This question bears semblance with the third research question posed in the "Introduction" section of this research. An efficient approach to increasing the participation of blacks and women in computing employment would be to recruit them onto pathways that have been proven to result in successful employment outcomes for them. This research has shown that attending an associate-degree-granting institution, possessing a traditional degree, having an internship, and possessing an alternative degree are educational choices that make up the most successful pathways. Therefore, national efforts should be targeted towards recruiting more blacks and women into community colleges. Educational schemes and programs that enable blacks and women to attend a community college and then transition to a four-year university should also be invested in.

At the high school level, school counselors should be equipped to guide black and female students toward a computing program at a community college. The counselors should also be privy to the educational programs that provide a community college to university pathway for students, so that students are aware of this pathway into computing. For students who are unable to attend community college, information about coding bootcamps and certification can be provided to them.

For students who proceed to community college and the university (through the proposed hybrid program), the program directors or undergraduate coordinators should provide students with internship and certification opportunities so that by the end of their program, they would have travelled the educational pathway that results in successful computing employment opportunities.

Limitations of the study

Using social media data for this research has its unique limitations. LinkedIn, as a corporate social media platform, holds only the data that users supply. Therefore, the data used in this research might not be reflective of the whole picture of a person's education and career path. In addition, the tediousness of this data gathering process has produced a small dataset because of the time and human resource constraint of this research. Because of the small size of this dataset, it is likely not representative of the general population.

Even though there are significant limitations to using social media data, social media data provides a unique opportunity, different from other data sources, to understand the pathways of women and blacks and to identify factors that result in their success in achieving and persisting in computing employment.

Conclusion

This research studied real-world data of working professionals, extracted from LinkedIn, in order to provide a picture of what educational choices and pathways have historically worked to provide successful computing employment outcomes for blacks (regardless of gender) and women (regardless of race), who are underrepresented in the field of computing. After carrying out some descriptive statistics, logistic regression, and predictive analytics, it was discovered that the majority of blacks and women did not do an internship, had a traditional degree, did not have an alternative degree, and attended a Rank1 institution. The data also showed that this popular pathway taken by women and blacks has not yielded the most successful computing employment outcomes for them. Rather, the most effective educational choices for successful computing employment outcomes are a Rank 3 institution education, possession of a traditional degree (degree ranging from an Associate's degree to a Doctoral degree), possession of an alternative degree (Certifications, coding bootcamp degrees, and other degree), and undertaking a computing internship. This result supports the recommendation[35] that BPC efforts should be targeted towards the upward transfer students (students who transfer from community colleges to 4-year computing college programs) since there is a high percentage of underrepresented students among the upward transfers. Not only is there a high percentage of underrepresented students on the community college-to-4year college track, but this pathway also has the highest probability of resulting in successful employment outcomes for underrepresented minorities (women and blacks, in particular).

References

1 McClelland, M., “Closing the IT gap for race and gender”. Journal of Educational Computing Research, 25(1), 2001, 5-15.

2 Peckham, J., L. Harlow, D. Stuart, B. Silver, H. Mederer, & P. Stephenson, “Broadening participation in computing: issues and challenges”, ACM SIGCSE Bulletin, 39(3), 2007, 9-13.

3 Doerschuk, P., J. Liu, and J. Mann, “Increasing participation of females and underrepresented minorities in computing”, Computer, 42(4), 2009, 110-113.

4 Hoffman, B., R. Morelli, and J. Rosato, “Student engagement is key to broadening participation in CS”. In Proceedings of the 50th ACM Technical Symposium on Computer Science Education, 2019, pp. 1123-1129

5 Bruckman, A., M. Biggers, B. Ericson, T. McKlin, J. Dimond, B. DiSalvo, ... and S. Yardi, " “Georgia computes!" improving the computing education pipeline”, ACM SIGCSE Bulletin, 41(1), 2009, 86-90.

6 Varma, R., “US science and engineering workforce: Underrepresentation of women and minorities”. American Behavioral Scientist, 62(5), 2018, 692-697.

7 Funk, C., and K. Parker, “Women and men in STEM often at odds over workplace equity”, 2018.

8 Shackelford, R., A. McGettrick, R. Sloan, H. Topi, G. Davies, R. Kamali, J. Cross, J. Impagliazzo, R. LeBlanc, and B. Lunt, “Computing Curricula 2005: The Overview Report”. Proceedings of the 37th SIGCSE Technical Symposium on Computer Science Education, 2006, p. 456.

9 Clear, A., A. Parrish, J. Impagliazzo, and M. Zhang, “Computing Curricula 2020: Introduction and community engagement”. In Proceedings of the 50th ACM Technical Symposium on Computer Science Education, 2019, pp. 653-654.

10 Exter, M., S. Caskurlu, and T. Fernandez, "Comparing Computing Professionals' Perceptions of Importance of Skills and Knowledge on the Job and Coverage in Undergraduate Experiences". ACM Transactions on Computing Education, 18(4), 2018
11 Carreon, C., "High school students will have faster pathway to computer science jobs through accelerated degree program". Northeast Mississippi Daily Journal (Tupelo, MS)., 2019
12 Commission on Higher Education & Employability, "Learning for Life and Work". New England Board of Higher Education, 2018, https://nebhe.org/info/pdf/policy/Learning_for_Life_and_Work_Report.pdf
13 Negoita, M., and K. Dunham, "Designing a Performance Measurement System for Career Pathways", 2013.
14 Workforce Connections, "Measuring Employment Outcomes" [PowerPoint slides]. https://youtheconomicopportunities.org/sites/default/files/uploads/resource/Outcome_Measurement_Event_Presentation_Feb_5_2015.pdf, 2015.
15 University of Washington, "What can students do to improve their chances of finding employment after college? Disabilities, Opportunities, Internetworking, and Technology". https://www.washington.edu/doit/what-can-students-do-improve-their-chances-finding-employment-after-college#block-menu-block-3, 2021.
16 Joyce. "Advantages & Disadvantages of Working for a Fortune 500 Employer". Job-hunt. Retrieved from: https://www.job-hunt.org/employers/Fortune-500/why-fortune-500-jobs.shtml
17 Brooke, V., and G. Revell, "Quality Indicators for Competitive Employment Outcomes & Indicator Form Fact Sheet", 2009. https://mn.gov/deed/newscenter/publications/trends/march-2014/employment-outcome-graduate.jsp.
18 Lindsay, J., and S. Babb, "Measuring Employment Outcomes for Workforce Development". USA; FHI 360, 2015.
19 Gawlowicz, S., "Policymakers urged to address concerns about US science and technology workforce (Rochester Institute of Technology)". Retrieved from http://www.rit.edu/news/story.php?id=45854, 2007
20 Smith, M., "Computer Science For All". National Archives and Records Administration. Retrieved from: https://obamawhitehouse.archives.gov/blog/2016/01/30/computer-science-all, 2016
21 Obama, B., "Obama initiatives would make America more competitive by investing in diversity" [Press release]. Retrieved from https://votesmart.org/public-statement/255254/obama-initiatives-would-make-america-more-competitive-by-investing-in-diversityindex#, 2007
22 Google (Firm) and Gallup (Firm), "Diversity gaps in computer science: exploring the underrepresentation of girls, Blacks and Hispanics", 2016.
23 Webb, D., A. Repenning, and K. Koh, "Toward an emergent theory of broadening participation in computer science education". In Proceedings of the 43rd ACM technical symposium on Computer Science Education, 2012, pp. 173-178.
24 Freeman, J., B. Magerko, D. Edwards, R. Moore, T. McKlin, and A. Xambó, "EarSketch: A STEAM approach to broadening participation in computer science principles". In 2015 Research in Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT), IEEE, 2015, pp. 1-2.
25 Whitney, T., and V. Taylor, "Increasing women and underrepresented minorities in computing: The landscape and what you can do". Computer, 51(10), 2018, 24-31.
26 DuBow, W., B. Quinn, G. Townsend, R. Robinson, and V. Barr, "Efforts to make computer science more inclusive of women". ACM Inroads, 7(4), 2016, 74-80.
27 U.S. Bureau of Labor Statistics. "Occupational Outlook Handbook: Computer and Information Technology Occupations". Retrieved from: https://www.bls.gov/ooh/computer-and-information-technology/home.htm, 2021.
28 Montandon, J., C. Politowski, L. Silva, M. Valente, F. Petrillo, and Y. Guéhéneuc, "What skills do IT companies look for in new developers? a study with Stack Overflow Jobs". Information and Software Technology, 129, 106429, 2021.
29 Someka Excel Solutions, "Fortune 500 Excel List". Retrieved from: https://www.someka.net/excel-template/fortune-500-excel-list/, 2020
30 ZipRecruiter, "ZipRecruiter Salaries". Retrieved from: https://www.ziprecruiter.com/Salaries, 2021
31 Indeed, "Indeed Salaries". Retrieved from: https://www.indeed.com/career/salaries, 2021.
32 Glassdoor, "Glassdoor Salaries". Retrieved from: https://www.glassdoor.com/Salaries/index.htm, 2021.

33 Sax, L., J. Blaney, K. Lehman, S. Rodriguez, K. George, and C. Zavala, "Sense of belonging in computing: The role of introductory courses for women and underrepresented minority students". Social Sciences, 7(8), 122, 2018.
34 Schwartz, "Minority and first-gen students feel greater belonging at 2-year colleges, study finds". Retrieved from: https://www.highereddive.com/news/minority-and-first-gen-students-feel-greater-belonging-at-2-year-colleges/569707/, 2020.
35 Blaney, J., "Broadening Participation in Computing: The Role of Upward Transfer". In Proceedings of the 51st ACM Technical Symposium on Computer Science Education, 2020, pp. 254-260.

Mercy Oluwadara Jaiyeola

Mercy Oluwadara Jaiyeola is an Assistant Professor of Computer Science at Hampden-Sydney College, Virginia. Her research interests are within the field of Computer Science Education with a focus on broadening participation in computing, studying the computing educational pathways and their effects on employment outcomes, employability of computing graduates, curriculum design and development for successful employment outcomes in computing, among others. She received her B.Sc. (Hons) in Computer Science from Bowen University, Nigeria; she received her M.Sc. (with distinction) in Computer Science from Liverpool Hope University, England; and she was awarded her PhD in Computer Science from Mississippi State University, USA.

Sarah B. Lee

Sarah Lee serves as Director of the School of Computing Sciences and Computer Engineering at the University of Southern Mississippi. Her research focus is in BPC. She holds a BS in Computer Information Systems from the Mississippi University for Women, a master's degree in computer science (CS) from MSU, and a PhD in CS from the University of Memphis.

Shahram Rahimi

Shahram Rahimi is Professor and the Department Head in the Department of Computer Science and Engineering at Mississippi State University. His research areas include Computational Intelligence, Machine Learning, and Predictive Analytics. He received his B.Sc. in Computer Engineering from Shahid Beheshti University and a master's degrees in Computer Architecture from Sharif University of Technology. He earned a masters in Computer Engineering Technology and a PhD in computational science from the University of Southern Mississippi.

Allen S. Parrish

Allen S. Parrish is Executive Director of the Alabama Transportation Institute and Professor of Computer Science at The University of Alabama. His research interests are in the fields of AI, Connected and Autonomous Vehicles, Data Science, Digital Transportation, and Machine Learning. He holds a BS in Computer Science from University of Tennessee, Martin, and he received a master's degree and PhD in computer science from The Ohio State University.

Michael Taquino

Michael Taquino serves as Deputy Executive Director at the National Strategic Planning & Analysis Research Center (NSPARC) at Mississippi State University. He earned his PhD in Sociology from Mississippi State University.