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But Where Will All the Women Come From? Tackling The Supply Side of Gender Diversity in the Technology Workforce. Why do (Female) Graduate Students Avoid or Take up 'Technology Oriented' Courses?

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04 December 2023 10:20:53

Abstract. To build and implement an inclusive technology, the AI workforce must be more diverse. The need for qualified technology professionals is growing along with AI's development, making inclusion even more important. The study has two primary research objectives: (i) To identify and understand the factors associated with student(female) decisions about whether to take up AI/ML/analytics/DS courses, and (ii) To suggest ways and methods that stakeholders (educational institutions) can adopt to motivate and facilitate students to take up AI/ML/analytics/DS courses. The present study is based on the Social Cognitive Theory (SCT) structure (Bandura,1986). The data was collected using four focus group discussions, and thematic analysis method was used for data analysis. The study provided in-depth analysis into the inclinations and inhibitions of students (male and female) to take up AI courses. The results also highlight the gender-based differences in the rational and reasons for choosing or giving-up AI courses as a career choice. The study findings reveal four broad themes: (a) personal, (b) contextual, (c) outcome expectations and (d) cultural. The study aims to identify and offer strategies that educational institutions and other stakeholders may use to encourage and enable women to enrol in courses in artificial intelligence, data analytics, and decision sciences.

INTRODUCTION

In today's digital economy, businesses, corporations, and communities at large are being reshaped by Artificial Intelligence (AI). AI includes – machine learning, expert systems, natural language processing, robotics, speech & vision recognition, planning & optimization (Samuel Greengard, Posted May 24, 2019). By making decisions more precise, facilitating easier living, and foreseeing trends that no one could have predicted, these technologies are promising to benefit society (OECD, 2020). In conclusion, AI has a significant impact and influence on people's behaviour in their everyday life. However, the prevent use of digital technologies is also causing ethical worries at the same time. Management consulting giant PriceWaterhouseCoopers reported, "AI, robotics and other forms of smart automation have the potential to bring great economic benefits, contributing up to $15 trillion to global GDP by 2030. However, it will come with a high human cost". According to the new McKinsey Global Institute report, by the year 2030 about 800 million lose their jobs to AI - driven robots. Apart from the popular and vocal challenges of AI leading to automation, replacing human jobs, labour issues, labour rights, and liberties – there are concerns about adding to, and reinforcing societal biases (Newman, 2017), such as those based on gender ethnicity, cognitive biases, stereotyping, cognitive manipulation, and so on (see Leavy, 2018; Raub, 2018; Noseworthy et al. 2020).

Given that these ethical challenges are subtle, overt, or deeply subconscious, that rarely attract the attention of the mainstream media or labour unions to foster rigorous discussions. In the aim to *'humanize'* AI, to make it more

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user-friendly and user-acceptable, we are adding human-like psychological and social aspects, thus bringing in our societal gender-role stereotypes/associations, which is further strengthening these gender biases. There are valid worries that artificial intelligence (AI) could exacerbate the imbalance and inequality between men and women in society and the workplace. Recent studies in the field of AI have called for ethical deliberations to comprehend and determine the moral obligations of AI and towards elimination of human biases, increased transparency, promotion of equity and inclusion (Accenture, 2018; Bano, 2018; Santamicone, 2019). Whether in the fields of finance, marketing, health, law, or the public sector, the usage of AI is growing exponentially, as are its applications. Making AI inclusive is much more important as a result. Inclusion, diversity, and equality of gender have made significant advances. However, allowing biases in Advanced technologies to continue would be the same as going back in time. An artificially intelligent bias happens when a computerised AI algorithm tends to make an irregular error solely for a particular group of people. For instance, compared to men, women have a larger likelihood of having a mistake made by an AI facial recognition system (Kompella, 2021). Automated decision-making tools are widely used and present in machine learning (ML) models. Clear racial and gender prejudices are present, with more and more women experiencing them (Datta, 2021).

The construction of algorithms is influenced and dominated by male experiences, with 78% of AI specialists being men. This discrimination based on gender may have serious negative effects for women. For instance, algorithms may restrict women's access to jobs and loans by screening their applications automatically or by assigning women applicants a poor rating. Like this, if the algorithm-based risk assessment in criminal justice systems did not take into account the fact that women are less likely than men to commit crimes again, it might work against women (Smith, 2019). The fact that Siri, Alexa, and Cortana are virtual personal assistants with female names and voices is not a coincidence. The businesses that provide these virtual assistants are supporting the social fact that women are disproportionately employed as personal assistants or secretaries in both the public and commercial sectors (UNESCO, 2022).

To build and implement technology that is inclusive, the AI workforce must be more diverse. The need for qualified technology professionals is growing along with AI's development, making this issue even more important. If things continue as they are, an AI labour market that does not adequately represent a diverse population will simply serve to exacerbate already existing disparities (Dillon & Collett, 2019). Research that examines the variables affecting diversity in technology workforce is necessary. While statistics are important, research should also focus on how to establish a sustainable culture of diversity that can be ingrained in workplaces and educational institutions (Dillon & Collett, 2019). To tackle the problem of gender diversity and representation in AI at its base and not only as a symptom; the AI sector needs closer linkages with academics and deeper academic collaborations (UNESCO, 2020). The fight for female talent inclusion and representation vitally depends on how they view the AI/data science courses, so it is crucial that higher education institutions recognise the need for female talent representation & inclusion and take appropriate action towards promoting it.

04 December 2023 10:20:53

AIM OF THE CURRENT STUDY

Given the context of including more women in the design and decision making processes of AI/ ML based systems (to make it more representative and bias-free), this study aims to identify and understand the factors associated with post graduate business school students'(female) decisions about whether or not to take up AI/data/analytics/decision sciences courses at the post graduate/Masters level in a University set up in India. Our study was developed with the goal of encouraging more females to pursue master's degrees and become significant participants in the planning, managing, and use of technology across various fields. The study involves Post Graduate/Master's level students becomes more and more significant to post graduate level students who have to make the decision to transition to workforce (Falco, 2017). With the help of this study, we hope to identify and offer strategies that educational institutions and other stakeholders may use to encourage and enable women to enrol in courses in artificial intelligence, data analytics, and decision sciences. The study has two primary research objectives: (i) To identify and understand the factors associated with student(female) decisions about whether to take up AI/ML/analytics/DS courses, and (ii) To suggest ways and methods that stakeholders (educational institutions) can adopt to motivate and facilitate students to take up AI/ML/analytics/DS courses.

THEORETICAL FOUNDATION

The present study is based on the Social Cognitive Theory (SCT) structure (Bandura,1986). In the 1960s, Albert Bandura developed the Social Learning Theory (SLT), which later became known as Social Cognitive Theory (SCT). The idea that learning happens in a social setting with a dynamic and reciprocal interplay of the person, environment, and behaviour was evolved into the SCT in 1986. The emphasis on social influence and on both external and internal social reinforcement is what makes SCT relevant in our study. SCT considers both how people acquire and sustain their behaviours as well as the social context in which those behaviours are used. The theory considers a person's prior experiences, which influence whether behavioural activity will take place. These previous experiences have an impact on incentives, expectations, and assumptions, all of which affect whether a person would engage in a particular activity as well as the motivations behind that conduct.

Using SCT, this study was undertaken to explore the reasons for female students to take up the specified courses, which may be personal, influenced by the external environment, society or any other significant reason that may guide them to decide. More precisely, this study aimed to confirm and add to the body of knowledge about the SCT theory's applicability to groups of people (Sheu & Bordon, 2017). This knowledge will supplement studies that develop the theory surrounding decisions about careers in analytics and data science at the post-graduate level in business schools, particularly women.

At this point we would like to clarify and state, for this study, we define professional AI/ML/Analytics/DS/IS occupations as analysts, programmers, computer managers, internet architects, webmasters, learning resources managers, and similar positions (Millar & Jagger, 2001). These positions call for qualifications such as a postgraduate degree in statistics or mathematics or economics or management, as well as functional and technical skills/capabilities in data science, machine learning, risk management, and analytics & insights. Accordingly, when we speak of pathways within formal education to these careers and roles at the business schools, we are referring to subjects from the Business School curriculum such as Management of Information Technology & Business, Information Technology for Business, Statistical Methods for Decision Making, Business Decision Modelling with Spreadsheets, Introduction to Business Analytics using R/Python, Blockchain and Cryptocurrency, Data Analysis & Interpretation , Introduction to Analytics, Introduction to Database Management Systems , Data Visualization, Advanced Business Analytics, Text Analytics and Technology Management. Therefore, we examined the intent of students wanting or not wanting to take up these courses, thus qualifying to an award of Analytics/ Information Systems major certification during the programme from the university. The students taking up these courses best fit the above-mentioned roles.

RESEARCH METHODOLOGY

Given the exploratory character of this study, we decided that a qualitative approach would be the most useful in helping us respond to our research questions. We collected data using four focus group discussions, and we used the thematic analysis method for data analysis. Focus group discussions according to Rubin and Rubin (2011), were utilised to create themes that are representative of both individual and group experiences. Focus group discussions can encourage individuals to share their thoughts and feelings (Lee & Lee, 2009).

We conducted Focus group discussions (FGDs for by dividing the four groups into 'Takers' comprising of students (both female and male) taking up data sciences/analytics /AI courses. The second group, 'non-Takers' comprising of students (both female and male) who did not/did not want to take these subjects. There were two groups each of 'takers' and 'non-takers'. There was a total of 24 participants (6-7 participants in each FGD). The students were between the ages of 20 and 33 years. 10 participants self-identified as male and 14 self-identified as female. We included females and male both in these groups as we thought it would help us give a contrasting view and delve on the differences between the two as well. Sometimes, a female is not able to come out with a reason for not doing something, but a boy's motivation on the other hand may help us identify a reason (for the female), by external observers like us. Additionally, the inclusion criteria were based on socioeconomically varied, gender-balanced students who would produce a wide range of outcome expectancies (Rubin & Rubin, 2011), and a sample size of between 5 and 7 participants for FGD is appropriate (Hill, 2010). All participants belonged to different places in India (namely Mumbai, Lucknow, Kolkata, Meerut, Sonipat) comprising of a fair mix of Tier I and Tier II cities. The FGD was guided by a protocol, covering areas and topics to be covered during the discussion (Mason, 2004). The protocol was based on the research questions framed earlier. The most convenient time and venue for students were chosen for

04 December 2023 10:20:53

the study's four 60-minute focus group discussions, each with six-seven participant. Two faculty members choose each group member to represent a variety of academic and socioeconomic backgrounds.

The FGD notes/recordings were transcribed and analysed using the Miles & Huberman Framework (1984). The interview data once collected was transcribed, coded, and manually compared for emerging themes, based on theoretical embeddedness of each theme. The qualitative data was inductively analyzed using Miles and Huberman (1994: 12) framework. This framework consists of three interacting activities are (i) data reduction, to 'sharpen, sort, discard and organize data' (ii) data display, 'in the form of easily understood configurations' (iii) drawing and verifying conclusions, 'draw meaning and check conclusion from the displayed data'. The results were coded by the researchers into higher-order themes. The emergent themes were compared with other common themes and this recursive process was continued until no new themes emerged. That is, until theoretical saturation was reached.

FINDINGS

The study provided in-depth analysis into the inclinations and inhibitions of students (male and female) to take up AI courses. The results also highlight the gender-based differences in the rational and reasons for choosing or giving-up AI courses as a career choice. Based on the results of the qualitative data analysis, the key findings of the study are discussed below as four emergent themes*:*(a) personal, (b) contextual, (c) career outcome expectations and (d) cultural.

The first theme identified as 'personal factors', was divided into two sections (i.e., gender, interests). The qualitative excerpts highlighted the that the choice of courses reflected a gender division or gender skewness towards male students than female students in analytical courses. One of the female respondents shared that *"courses like gamification or SQL programming, we have more guys in the class as they are into gaming; however, in courses like HR or entrepreneurship, we had a fair mix of boys and girls in the class."* Another male respondent shared that *"most of the drop outs from the gamification course were girls, I don't know the specific reasons but that surely impacted the diversity of class".* Another male respondent shared that *"I read about data analytics in school…and it sounded so cool to me...that's when I developed interest in the field", and* yet another male respondent quoted that *"I set up my own PC, I fixed up my own laptop, that's like these are the kind of things that I've always been into…I was natural to analytics".* One of the female respondents quoted that *"I didn't join the course because I don't want to do back-end work, like these programming and analytics are more like back-end work…I am rather more interested in front-ended customer facing roles…Not because analytics is technical…"*

The second theme identified as 'contextual factors' has four subcategories (i.e., teacher support, family influences, childhood dream jobs, perceived academic aptitude). The qualitative excerpts highlighted the need for teacher support during school and college days. One of the respondents shared that *"it was only in college that she heard about analytics and/or AI"* however, another respondent shared that *"they had basic analytics courses at school which made him interested to further pursue the course at college".* The qualitative excerpts highlighted that few female graduate students felt intimidated by the courses, even when they know that analytics is a booming field. One of the female respondents stated that "*...it was a little intimidating for me, so I don't think I'll be going forward with it, but I am sure like it's (AI) is a very up and coming field ...".* Another female respondent shared similar self-efficacy issues that *"I think there's an opinion that I am not well suited for it. For me personally, it's difficult and I feel, I don't have the skill or the aptitude for it."* One of the male respondents quoted that *"you have to be an above average student, if not a nerd…to do well in these courses."* Another female respondent shared that *"I was weak in Maths during my school days so I didn't t think of choosing analytics in college…but when I did some compulsory courses in first year of college ..SPSS and other software I understood that it wasn't all about numbers…it was logic, and I did well on them"*

The third theme identified as 'career outcome expectations' was divided into two categories (i.e., job market trends, high paying jobs). The qualitative excerpts highlighted the positive career outcomes of choosing AI/Analytics. One of the female respondents stated that *"the industry is booming, and I know that analytics is the industry requirement. Everyone is getting into business analytics and AI."* Another female respondent shared that *'AI and machine learning are upcoming fields with good employment opportunities…and I am told to develop interest in this field'.* Another respondent quoted that *"it is good money; I am going for it."*

04 December 2023 10:20:53

The fourth theme identified as 'cultural factors' was further divided into three categories, (i.e., social influences in a predominantly patriarchal society, impact of media, representation & role modelling). The qualitative excerpts highlighted the One of the female respondents stated that *"the field seems very interesting, but I don't know how to proceed with it, I mean I can't see how that career will plan out for girls like me...(someone with non-technical background)"* Another male respondent shared that *"for me this field is more technical and more about data and its analysis, be in business or otherwise. You know numbers cannot go wrong."* Highlighting the need for female role models, one of the respondents shared that *"I was very hesitant to take up analytics in my first year. But then, when did a few courses with Prof Shalini and Prof Divya (female professors), my comfort level with the courses help me take more courses in the second year"* Another female respondent quoted that *"the media has glorified these fields so much that if you are majoring in analytics or AI...people are like Oh, Nice!!"* One of the male respondent shared that *"my brother was in the analytic field, and he was doing well, which kind of sparked my interest in the field as well"*

The findings also unravel some of the myths regarding AI related courses and careers that have strengthened over years due to lack of female role models and representation in the field. The emergent themes provide evidence that factors influencing the decision to take AI related courses/career are significantly different in female students as compared to their male counterparts. Thus, providing implications for educational institutes on how to attract more female students towards AI-related courses.

IMPLICATIONS & FUTURE RESEARCH DIRECTIONS

The present study contributes to the body of knowledge and to practise.

First, FGDs offers a thorough comprehension of people's inner experiences (Hill et al., 2005). We can learn more about how graduate students decide on a AI/IS/Analytics career in cultural setting like India by using the findings of this study. Personal and contextual factors are two areas that need more cross-cultural research (Sheu & Bordon, 2017).

Second, since students received more career guidance material from media (including the internet), it is crucial for educational institutions to be aware of the media that may be influencing students' choices. Additionally, it appears that students are shifting their views on the traditional professional value, which in the present day prioritises "jobs not only as professions but also contributing to a cause" At this time, counsellors / educational institutes can assist kids in focusing on positive outcome expectations and boosting their self-efficacy by organising activities like college fairs, college visits, career assessments, and role models and mentors when they voice worries about career interests and objectives (Lapan & Kosciulek, 2001). The impact of media on high school students' professional interests and ambitions may be studied by future scholars. Researchers might also investigate how media, as well as perceived barriers and supports from families, influence how people make job decisions across cultures.

Third, based on our research, we have made some concrete recommendations that educational institutions may find valuable to put into practise in the future to encourage females to enrol in AI/ML/data sciences/IS courses. Some of these include: a) increasing the visibility of women and female students in all public relations materials for the institution (such as information folders) and at various events (such as Open Houses/University Days); b) altering the descriptions and titles of some technical courses to emphasise on results rather than technology; c)training faculty instructors on gender-fair teaching; d)having more female faculty instructors teaching these particular courses; and e)starting collaborations with tech companies to conduct workshops in order to get across that "technology is not geeky."

LIMITATIONS

The study has several limitations. Firstly, as the study focused on group conversations with business school students to capture the depth of individual viewpoints on AI, data sciences, and IS job development, these findings cannot be applied to all Indian students. Additionally, this research approach does not provide conclusive answers regarding the relationships between themes and variables. Third, since they were aware they were being interviewed and filmed, participants might have given information about what they believed to be the best career development

04 December 2023 10:20:53

paths. Additionally, in a focus group, participants could experience peer pressure to provide similar responses to the facilitator's queries. Finally, each group interview lasted 60 minutes, with an average participation time of 10 minutes per kid. Our ability to fully capture the breadth of the students' experiences and perceptions may have been constrained by their briefness.

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04 December 2023 10:20:53