Measuring the Impact of AI-related Attitudes, Awareness, Skills and Usage on Students' Learning Experience: A Gender-Based Exploration

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International students, particularly in U.S. STEM graduate programs, often rely on artificial intelligence (AI) for translation, grammar, and writing aid. These programs have historically seen low female representation, reflecting a global gender gap in STEM education and technology usage due to systemic inequities. This study explores gender-based differences in AI-related dimensions and their impact on international students' learning experience. Using Necessary Condition Analysis (NCA), we examined AI awareness, usage, perceptions, and education as predictors of positive learning outcomes. Surveying 422 Indian STEM students at a southeastern university, we found no gender-based differences across AI categories. Except for AI awareness, which proved a poor predictor for both genders, all other AI-related dimensions emerged as significantly necessary for higher learning experiences. These findings challenge existing research on the digital gender gap, offering implications for faculty and higher education administrators. We also discuss study limitations and propose future research directions.

Keywords: artificial intelligence, educational technology, higher education, STEM, gender-gap, necessary condition analysis

INTRODUCTION

International students are increasingly attracted to U.S. colleges and universities, with a noticeable majority of students that come from India. Recent data suggests that India has surpassed China as the U.S.'s leading source of international students (Venkatraman, 2024). Moreover, a record number of students from India are also enrolled in science, technology, engineering, and mathematics (STEM) graduate programs at U.S. institutions of higher learning. Their number approaches 197,000, a 19 percent increase from the previous year (U.S. Embassy, 2024). The appeal includes both enthusiasm for a U.S. education and the fact that students enrolled in approved STEM fields may be able to extend the time they are eligible to work in the country. Yet, once in the U.S., these students tend to confront obstacles centered around cultural and language barriers that contribute to other challenges of graduate school.

For the non-native English-speaking international student, artificial intelligence (AI) can help bridge language barriers and aid with other academic challenges. However, inequities in the understanding of and experience with AI may lead to differences in AI adoption levels, and in turn to differences in educational outcomes. Recent research supports the contention that AI may contribute to exclusion of women and to educational disparities for international students (Bulathwela et al., 2024; Perkins et al., 2024). Differences in the use of AI-related academic tools are likely to also contribute to inequities in overall educational outcomes. For instance, research suggests that females are significantly less likely to use AI compared with their male counterparts (Aldasoro et al., 2024; World Economic Forum, 2024). Furthermore, gender-specific differences around AI trust and perceptions of AI have resulted in usage disparities with male students more than female students inclined to use AI for education, including learning of a foreign language (Armutat et al., 2024; Dolenc & Brumen, 2024).

In light of these reported gender-based inequities, we sought to investigate the possible impact that AI-related dimensions – attitudes, awareness, skills and usage - may have on graduate students' learning experience, with an eye on possible gender-based differences. In particular, we sought to find answers to a few questions: Does artificial intelligence matter for either male or female students? Is AI a hinderance or a facilitator of learning for either gender? Can AI-related attitudes and awareness serve as predictor of positive learning experience for both male and female students? How do AI-related skills and usage affect male and female students' learning experience? Ultimately, should college administrators and faculty encourage using AI tools in educational settings and beyond? Thus, the purpose of this research is to examine the potential impact of AI awareness and understanding (AU), experience and usage of AI (EU), perceptions and attitudes toward AI (PA), and AI skills, education & training (SET) on student learning experience, while ascertaining possible gender-specific differences between male and female graduates. Studying a sample of 422 international graduate students from India in STEM programs at a southeastern university, we utilized a necessary condition analysis to explore gender-based necessity conditions among the mentioned set of AI-related dimensions - AU, EU, PA, and SET - as predictors of overall students' positive learning experience. Results revealed no gender-based differences across all four categories. Specifically, except for the AI awareness-understanding dimension, which was found to be a poor predictor of learning experience for male and female students alike, all other AI-related dimensions emerged as statistically significant predictors of a positive learning experience for students of both genders.

THEORETICAL FRAMEWORK

Two main theories provide the theoretical foundation for this study. We drew on the Technology Acceptance Model and on Conservatism theory. Much of the research on technology and AI has relied on the Technology Acceptance Model (TAM) framework, which was initially developed by Davis (1986, 1989). TAM is based on three overarching constructs: perceived ease of use, perceived usefulness, and attitude toward using technology that could be used to predict users' motivation to adopt technologies. The TAM continues to expand to include emerging constructs widely used in educational technology acceptance studies. An Extended Technology Acceptance Model added six additional constructs related to academic contexts, including academic experience, ease of access to materials, perceived ease of use for collaborative learning, lecturer's positive response, expectation of academic achievement, and self-efficacy (Venkatesh & Davis, 2000). While specifically related to digital reading tools, their research indicated the most significant effect sizes are associated with attitudes influencing intention to use, with self-efficacy on perceived ease of use, and with the perceived ease of use on perceived usefulness. We consider TAM's emphasis on user's technology usage, experience and attitudes to be highly relevant to our investigation as all three concepts are also central to the AI-related dimensions in our study. Moreover, TAM's added construct of self-efficacy is well aligned with a key facet of conservatism theory that appears to also serve well this study's theoretical foundation.

As suggested, this research is equally viewed through the lens of constructivism theory. The theory asserts that learning is influenced by how things are taught as well as by students' beliefs and attitudes about learning (Bada & Olusegun, 2015). Rather than view the learner as a passive recipient of knowledge, a central tenet of constructivism views the student as active participant in their own learning process (Tan, 2000). Constructivist learning theory supports the idea that certain attitudes and perceptions drive learning behaviors that can contribute positively to the student learning experience. For example, student-regulated learning, which is the use of self-generated actions that contribute to learning, has been shown to result in increased academic achievement and confidence in their abilities to succeed (Usher and Pajares, 2008; Joo et al., 2000). Better known as academic self-efficacy, the concept has been positively associated with academic achievement and quality of learning experiences in secondary school students (Stankov et al., 2014), in higher education students on campus and in online learning courses (Kuo, 2010; Gunawardena, 2010), in blended learning courses (Prifti, 2022), and in undergraduate STEM programs (Kryshko et al., 2022). In fact, much of the literature on student retention and satisfaction highlights the importance of self-efficacy for a successful learning experience. Educational research related specifically to AI self-efficacy indicates that the ability to process and create information using AI positively influenced attitudes toward learning activities (Jia and Tu, 2024; Moriyama et al., 2009) and increased learning motivation (Jia and Tu, 2024). Furthermore, students with high self-efficacy showed significantly higher enjoyment from and investment in learning activities that are associated with overall quality of educational experience (Bassi et al., 2006). Building on self-efficacy and self-regulated learning concepts, we assert that regardless of potential gender-specific differences, the mere fact of pursuing an academic degree in a foreign country places the international student in the camp of active participants in their own learning journey. Support for this argument might lend credence to tenets of conservatism theory, thus making it more relevant to our own investigation.

REVIEW OF THE LITERATURE

Integrating AI in Higher Education

AI is a broad term that includes many sub-fields and tools widely adopted for use in higher education settings. Generative AI is a widely utilized subset of artificial intelligence that can create new content through existing data via user's prompt engineering. This innovative tool has brought numerous challenges and opportunities to higher education. Among these challenges is the fact that generative AI can be used to respond to exam questions and generate essays, making it easier for students to cheat without being easily detected (Michel-Villareal et al., 2023; Coffee, 2024). A report by Wiley indicates that approximately 68% of instructors believe that AI will hurt academic integrity (Coffee, 2024). Certainly, preserving academic integrity is critical; nearly half of students in a recent survey indicated that AI makes cheating easier (Coffee, 2024). In what has been referred to as the "wild west," educators and administrators are struggling to manage its use and uphold academic integrity standards.

Many higher-education students rely on AI in their academic studies regardless of the potential consequences. A recent survey indicated that 86% of university students use AI in their studies (Kelly, 2024). The fundamental concern has been that student reliance on AI to complete coursework undermines meaningful learning and erodes the foundation of academic integrity. However, AI is not being used solely for cheating. In fact, a recent large-scale national survey of young adults (Common Sense Media & Hopelab, 2024) found that the most commonly reported uses of AI were to get information (53%) and brainstorm (51%). Non-native English-speaking international students may rely on AI for translation and language learning; access to AI resources such as translation, writing, and language learning tools can help non-native English-speaking students better navigate their academic studies (Wang et al., 2023; Nurmayanti et al., 2023). Natural language processing and machine learning models can be used to analyze text, correct grammar, and translate from one language to another. Thus, students for whom English is not their first language may rely heavily on AI tools for academic success. One can then reasonably assume that students who cannot fully utilize these innovative tools may potentially be at a disadvantage compared to their peers.

The Digital Gender Divide

The digital gender divide is a term used to describe inequalities experienced by women across the globe related to digital access and skills (Dixon et al., 2014). Early works suggested that the digital gender divide is not a universal phenomenon presented in the literature but appears unique and specific to each particular country (Varma, 2009). More recent works provide support for this argument. For example, Singh (2018) indicated that in many countries, the gender digital divide is more pronounced due to restrictive social norms and social inequality. For India and some other developing countries, this appears to be the case; consider that a report to the United Nations Population Fund (UNFPA) indicates that based on a recent survey, there are certainly restrictive social norms and inequality for Indian women related to technology access and both digital and functional literacy (Jejeebhoy, 2024). Regardless, India and other developing countries have shown a large increase in women in STEM programs. In fact, India has one of the highest percentages of women in STEM education programs worldwide (Kumar, 2024). Globally, STEM majors have historically been dominated by males with females vastly underrepresented. The reasons for this include the idea that STEM careers have been traditionally considered to be masculine and females are either steered away from these fields by parents or teachers. In fact, the perpetuated bias that women cannot perform well in math may inform their lack of confidence in their ability to succeed in STEM fields (Lubienski et al., 2013). As a result, females may not consider STEM majors to be an attractive option.

Yet, these inequities can be overcome as many countries have started to address the digital gender divide through educational programs and policy changes. India, in particular, has made significant progress in gender equality in STEM education through government interventions, programs and community efforts in recent years, encouraging female students to enroll in STEM programs, which have increased enrollment. According to the Center for Security and Emerging Technology, India boasts one of the highest percentages of STEM graduates globally, second only to China (Oliss et al., 2023), and one of the highest percentages of female STEM graduates worldwide which is nearing parity at approximately 43 percent (World Bank Group, 2018). However, research indicates that there are still significant gender disparities for women in educational enrollment and literacy rates (Baidya and Jayalakshmi, 2024). Globally, females have been typically underrepresented in STEM fields, which has been a continuing concern for educators and policymakers alike.

Artificial Intelligence and Learning

There is a growing body of literature that supports the positive influence of student use of AI digital technologies on learning motivation (Ali et al., 2023; Huang et al., 2023: Neji et al., 2023), on the desire to learn the technology (Chiu et al., 2024; Lin et al., 2021; Murakami et al., 2024) and on student positive learning experience (Xu, 2024). Such learning experience is highly related to attitudes toward learning and the perceived value of what is being learned, both of which drive a student's academic performance (Cybinski & Salvanathan, 2005). Thus, one can assume that differences in students' AI-related attitudes, usage, knowledge, and skills are likely to result in different perceived learning experiences. We briefly expand on this argument with a review of relevant literature concerning these AI-related dimensions which we view as possible predictors of student's learning experience.

AI Training, Education and Skills

Students are seeking AI-related training, yet many are not getting it. A recent survey published by Inside Higher Ed indicated that 72 percent of respondents believe higher education should prepare them for AI use and application in their careers (Flaherty, 2024). Respondents indicated that the topic they thought was the highest priority was the ethical use of AI, with critical-thinking and problem-solving reported as important to them. Integrating AI training into the higher education curriculum may provide students with an overall positive learning and with the experience they need to be career-ready. Moving in that direction is critical given that by some estimates less than 10 percent of students indicated that their institution offered any training on AI (Flaherty, 2024). In addition, there were substantial differences in students who used AI for coursework. Students at public institutions were almost twice as likely to use generative AI for coursework and students over 25 were less likely to use it. Those in community college programs were also more likely to indicate that they did not have AI knowledge (Flaherty, 2024). As for AI-related skills, these include programming, prompt generation, data analytics, and understanding algorithms. These skills are no longer only reserved for students in technology majors. These skills are becoming increasingly in demand in all college majors as commercial and public sectors expand their use of AI technologies. The Federal Reserve Bank of Atlanta reported the demand for AI skills is increasing rapidly and is no longer limited to STEM fields as it is also quickly expanding into a large portion of non-STEM occupations and industries (Mohnen & Lee, 2024).

AI Usage and Experience in Education

Generative AI utilizes algorithms to generate unique outputs from data, and tools such as ChatGPT make it relatively easy for students to generate content for assignments, exams, and essays and pass it off as their own work. This has been a thorny issue and the reason behind the resistance to AI use in higher education. Yet, there are a variety of ways that students can use AI in academic coursework to support and control their own learning experiences while still upholding standards of academic integrity. A recent large-scale national survey of young adults (Common Sense Media & Hopelab, 2024) found that the most commonly reported uses of AI were information gathering (53%) and brainstorming (51%). AI chatbots emerge as valuable for providing tutoring and feedback to students in real time (Xu et al., 2019).

Also, many non-native English-speaking students rely on AI for translation, language learning (Ericsson, 2023; Yang & Kyun, 2022), and assistance with grammar and spelling (Dizon & Gayed, 2021). The perceived usefulness of AI in classwork is positively related to student satisfaction (Almulla, 2024; Boubker, 2024) and linked to the efficiency of work and timely responses to questions (Zhang et al., 2024). GenAI can also provide students with a great deal of information and be used for fact-checking, grammar and syntax correction, spelling, idea generation, translation, and generation of research resources. In a review of the San Diego Student Survey data of more than 10,000 students, more than 81 percent of students indicated that they use ChatGPT, 62 percent indicated that they use Grammarly, and more than 48 percent of students indicated that they use AI tools or applications in their academic studies (SDSU, 2024).

Yet, inequities in usage and experience with AI may lead to differences in its level of adoption for supporting academic studies and is likely to result in differences in educational outcomes and experiences. Recent research suggests that differences in the level of AI-related experience may contribute to exclusion and educational disparities for older students (Flaherty, 2024), for women as well as for international students (Bulathwela et al., 2024; Perkins et al., 2024). Male students and students from technology programs have been shown to have greater optimism about AI technology and thus, a higher level of AI use (Stohr, 2024; Joseph et al., 2024).

AI Perceptions and Attitudes

Student usage of AI is driven in part by their perceptions and attitudes towards the technology but may also be influenced by fear of violating institutional or classroom policy. Believing that AI is used for cheating has compelled some educators to focus heavily on identifying offenders by using AI detection tools that have been shown to be unreliable. Because the detection of AI in academic coursework is based on imperfect algorithms that examine complexity and variability in writing, it can produce inaccurate results. For international students this may pose an even greater risk. They have been shown to disproportionately face false accusations of cheating with devastating consequences (Liang et al., 2023). For one, it has created an environment of fear and distrust in the classroom that can potentially disparate impact non-native English-speaking international students, making some reluctant to use it in academic work. Users have also indicated some concerns about AI's limitations and ethical concerns about data privacy; both issues have been frequently discussed in the literature. Omrani et al. (2022) data from more than 30,000 respondents indicated that many of the concerns around AI were related to trust. However, results are mixed on whether trust significantly impacts the use of the technology. Choung et al. (2023) found an indirect influence of trust on the intention to use AI. However, Menard and Bott (2024) found that concerns over both trust and risk did not significantly affect the use of AI technology. Perceived ease of use (Shaengchart, 2023), user-friendliness (Maheshwari, 2024), lack of information quality (Tan et al., 2024; Shoufan, 2023), and a lack of ability to generate profound insights (Liu & Zhang, 2024) have also been shown to influence attitudes of AI use. We assert that attitudes may influence students' use of AI, which can impact their learning experience.

AI Awareness and Understanding

Awareness towards AI technology is relatively high amongst university students (Joseph et al., 2024; Ampofo el al., 2023; Dergunova et al., 2022). However, research reports that the majority of university students lacked sufficient understanding of the technology and how it could be used. Interestingly, lack of understanding is common across several different countries. For instance, a study of Nigerian students indicated that most students were unaware of AI technology for learning (Alimi et al., 2021). Similar findings were reported in India (Ahmad et al., 2024), Australia (Kelly et al., 2023), and Turkey (Yuzbasioglu, 2021). Several studies explored gender differences in AI awareness. While no gender differences were identified in students in the Sultanate of Oman (Simon et al., 2024), Joseph et al. (2024) found that male students in India had a stronger awareness of AI tools than their female counterparts. Thus, one can assume that students who know and understand how to use AI technologies will be more likely to apply them in academic work to enhance their learning experience. A recent study used the TAM model to assess whether ChatGPT awareness and adoption intention were significantly mediated by perceived ease of use, usefulness, and intelligence in Chinese university students (Shahzed et al., 2024). The findings suggest that high ChatGPT awareness strengthened the connection between perceived ease of use, perceived usefulness, and perceived intelligence; awareness of the technology ultimately positively influenced their knowledge and skills, making them more likely to adopt the tool to enhance their self-learning (Shahzed et al., 2024).

Reflecting on the preceding literature review, we formulated several key hypotheses for study. We consider each hypothesis to hold true for both genders. Also note that the phrasing we use for the four hypotheses is consistent with NCA convention and terminology:

H1: *A high level of AI-related skills and training is necessary for a high level of perceived positive learning experience of male and female STEM grads.*

H2: *A high level of AI-related usage and experience is necessary for a high level of perceived positive learning experience of male and female STEM grads.*

H3: *A high level of positive AI-related perceptions and attitudes is necessary for a high level of positive learning experience of male and female STEM grads.*

H4: *A high level of AI-related awareness and understanding is necessary for a high level of positive learning experience of male and female STEM grads.*

Necessary Condition Analysis (NCA)

A brief explanation of NCA's functions is essential for the reader who is not familiar with this novel statistical analysis approach. A key function of NCA is the scatter plot. Rather than draw a regression line through data in a scatter plot, NCA looks for empty spaces in the upper left-hand corner of the plot and draws a ceiling line "on top" of the data. Lines border the 'empty space' and the 'full space' of the data-set (Dul 2020). In our case, (see Figures 1and 2 under results), lines indicate the degree to which learning experience (y-axis) could be ensured without the presence of specific antecedent factors (x-axis). In other words, the ceiling line marks the boundary between the zone with and without observations. The larger the empty zone, called the ceiling zone (C), the larger the constraint that the condition (i.e., attitudes, skills, usage and awareness) puts on the outcome (i.e., learning experience). Thus, the size of the ceiling zone compared with the size of the entire area that can have observations (i.e., the scope, or S) represents the effect size of a necessary condition. The effect size is expressed as $d = C/S$ with d being the effect size. The range of d can be from 0 to 1 ($0 \leq d \leq 1$). Dul (2020) suggests the following thresholds: $0 < d < 0.1$ is considered a small effect, $0.1 \leq d < 0.3$ is considered a medium effect, and $0.3 \leq d < 0.5$ is considered a large effect, and $d \geq 0.5$ is considered an exceptionally large effect. Thus, the effect size of $d = 0.1$ has been used as a threshold to consider an effect as theoretically and practically meaningful (Dul, 2020). NCA requires and allows the researcher to perform approximate permutations, typically about 10,000, to test for statistical significance (Dul, 2020). This permits the researcher to identify a meaningful necessary condition, when the effect size d is larger than 0.1, and is statistically significant with a p-Value smaller than 0.05.

An additional comment relating to ceiling lines is warranted. NCA presents two recommended ceiling lines: ceiling envelope (CE) and ceiling regression (CR). The CE technique – a ceiling envelopment with free disposal hull (CE-FDH) - assumes that the ceiling is non-decreasing, resulting in a non-decreasing step function (see Figures 1 and 2 under results section). CR 'smooths' the linear function obtained by the CE technique; thus, CR- FDH draws a line through the CE-FDH corners (see Figures 1 and 2). According to Dul (2020), given that the CE-FDH is more flexible and does not require many assumptions, it is the recommended ceiling technique for dichotomous and discrete necessary conditions. CR-FDH is recommended for continuous necessary conditions.

Finally, interpreting NCA results can be facilitated by the use of bottleneck tables, which are particularly helpful when one wants to analyze multiple necessary conditions for the same outcome; in our case, assessing the necessary conditions of a set of AI-related dimensions for higher levels of a student's learning experience be it a male or a female one. A bottleneck table is a tabular representation of the ceiling line of our multiple NCA's necessary conditions. It indicates which level of a necessary condition is needed for a certain outcome level, according to the ceiling line. Table 5 (see results section) shows a bottleneck table for each gender. The outcome levels are expressed as a percentage of the observed range: 0 is the minimum observed value, and 100 the maximum observed value. The condition levels are also expressed as a percentage range, thus suggesting which high levels of Y can only be achieved with a certain level of X. Unless these minimum levels of X are achieved, the various levels of the outcome will not occur. While NCA application has been used in various studies conducted in different fields, such as in logistics, HRM, education, entrepreneurship, tourism, and international business management (e.g., Malka & Austin, 2024; Richter, Schlaegel, van Bakel, and Engle, 2020; Tynan, Credé, and Harms, 2020; Wangoo and Jeong, 2021), we are not aware of any other work that has used NCA in an AI-related study.

Method

We seek to investigate the effects that AI-related attitudes, awareness, skills and usage have on graduate students' learning experience, focusing on possible gender-based differences. We hope to answer a few questions: Does artificial intelligence equally matter for male or female students' learning experience? Is AI a hinderance or a facilitator of learning for either gender? Are AI-related attitudes and awareness equally necessary for male and female students' positive learning experience? What are the effects of AI-related skills and usage on male and female students' learning experience? Should college administrators and faculty encourage the use of AI tools in educational setting and beyond?

Sample

The sample is drawn from the universe of graduate STEM students in a southeastern university. Included in our sample are active students that have enrolled in various STEM courses during the 2024 school year. The bulk of these students are international students who arrive primarily from India. Our preliminary estimate suggests that the total number of such participants is nearly five hundred. With the approval of the study by our institution's IRB, we began with data collection and ceased soliciting additional surveys once we reached four-hundred and fifty returns. Twenty-eight surveys were found to be incomplete and were thus eliminated. Of the four-hundred and twenty-two complete surveys, two-hundred and ninety-eight were male STEM grads, and one-hundred and twenty-four were female STEM grads. We captured some of our graduates' demographics in Table 1.

TABLE 1
SAMPLE CHARACTERISTICS

Gender	**N**	**%**
Male	298	70.6
Female	124	2934
Age Group		
<21	9	2.1
22–34	393	93.1
35–44	19	4.5
45–64	1	0.23
>65	0	

(n=422)

Measures and Sample Items

We collected data from graduate students in STEM fields using a tested pre-existed questionnaire at a single point in time. The SDSU Student AI Survey Instrument (Goldberg et al., 2023) was utilized with a slight modification. Since exploring students' ratings of AI-related dimensions and relevancy to their current learning experience is the aim of this study, we eliminated the Future Expectation of AI section. Being of little value for NCA, we also removed the optional open-ended questions. The instrument includes a total of 26 questions on AI-related awareness and understanding (AU); AI-related skills, education, and training (SET); perceptions and attitudes toward AI (PA); and AI-related experience and usage (EU). The multiitem questionnaire employs a 6-point Likert-type scale, from 1= = strongly disagree to 6 = strongly agree. The subscales of the instrument were tested for reliability with Cronbach alpha coefficients at an acceptable range between 0.69 and 0.74. The four AI-related dimensions of AU, SET, PA and EU represent the study's independent variables ($\mathbf{X_1}$ through $\mathbf{X_4}$). Learning experience is the study's dependent variable (**Y**). For X_1-X_4, the aim is to solicit the degree of agreement from graduates with respect to each statement, and as it applies to graduates' current course work.

For our Y, the aim is to solicit graduate agreement on the overall impact of the AI-related dimensions on their learning experience. For the study's X_1-X_4, a sample of statements under the Awareness/Understanding dimension include – 1. I regularly follow news and updates about AI – 2. I regularly discuss AI topics with friends, family, or classmates. A sample of statements under the Experience/Usage dimension include – 1. I use AI-powered tools or applications in my studies – 2. AI-powered tools are essential for my academic success. A sample of statements under the Perceptions/Attitudes dimension include – 1. AI has the potential to reduce human biases – 2. AI can contribute positively to social issues. Finally, a sample of statements under the Skills/Education/Training dimension include – 1. I am interested in receiving formal training in AI through coursework or other resources – 2. I am actively seeking opportunities to learn more about AI. A sample content area item for the study's Y includes – AI has positively affected my learning experience. A stated above, graduates rate these items, and all other items, on a six-point Likert ranging from "Strongly Disagree" (1-point) to "Strongly Agree" (6-points).

Procedure

The entire universe of recent STEM program graduates, during the preceding 2024 year, has been targeted via direct email. The university's College of Business and Technology obtained graduates' names and email addresses. An online opt-in invites to take part in the early study was posted to members of our sample, with an explanation as to the purpose of the study, as well as to the researchers' ensured anonymity and expressed interest in aggregate data only. Members who choose to participate gained access to the survey via a designated link to a Qualtrics-based questionnaire, as the means used to collect the data. Thus, within the context of the study's focal unit and theoretical domain, STEM program graduates during 2024 serve as our data informants. Calculating a sufficient sample size of n = 400, we ceased solicitation once a threshold of 450 surveys were returned of which 422 completed questionnaires were confirmed, thus establishing our final sample size (n=422). In our current context, we seek to use NCA to study the effects of said variables from a fresh angle, hence hoping to shed new light on the necessity conditions as stated in the above formulated necessary hypotheses with an eye on possible gender-specific differences.

We performed analysis of data collected in one step: NCA was used for ascertaining relationships amongst the study variables across two gender-based sub-samples (n=298; n=124, respectively) regardless of participants' age. And since NCA is fundamentally a bivariate analysis method, only one X and Y are analyzed at a time. We intend on using the ***scatter plot*** approach, and given the nature of our data, we intend on showing both NCA ***default lines*** (s) - the step line CE-FDH in case data around the ceiling is irregular, and the line ceiling regression CR-FDH given the continuous nature of our data. The plots are expected to show no cases in the empty cell at the top left corner of each plot, thus validating our assertion of necessary conditions as hypothesized. We set the ***effect size*** (d) threshold at a level that is less than or equal to 0.5. Namely, small to medium effect size (Dul, 2020). In addition, we set a statistical significance ***p*-Value** at less than or equal to 0.05, for the effect size with 10,000 permutations; this allows us to gain accurate ***p*-Value** estimates as recommended (Dul, 2020). Finally, we intend on calculating ***bottlenecks*** and presenting results in a bottleneck table**.**

Results

Figures 1 and 2 depict scattered plots based on data collected from our sub-samples for male and female grad students. Specifically, Figure 1 and Figure 2 show plots of our four independent variables (X_1-X_4) and the constraint that each X have on the learning experience (Y) of grads in each sub-sample, respectively. A visual inspection of each one of our eight scatter plots points to the existence of a noticeable empty space in the upper left corner of six out of eight plots. The small size of the empty space for Awareness/Understanding plot, for either male-female in our sub-samples, suggests a negligible constraint, if any, of this variable on our dependent variable (Y). The lack of constraint in this case also points to lack of necessity, or relevancy of AI-related awareness and understanding for students' learning experience regardless of graduates' gender. Also noticeable is the fact that there are no cases above the CE-FDH red-dotted line, and that only a negligent number of cases are visible above the CR-FDH yellow line in both sub-samples. Thus, suggesting a high level of X is necessary for a high level of Y as envisioned by NCA. Using both ceiling lines with our plots supports the robustness of our analysis since it allows for the comparison of results. However, given space constraints here and the continuous nature of our data, we only present CR-FDH results as depicted in Table 2, the NCA quantified parameters.

FIGURE 1
SCATTER PLOTS-MALE GRADS

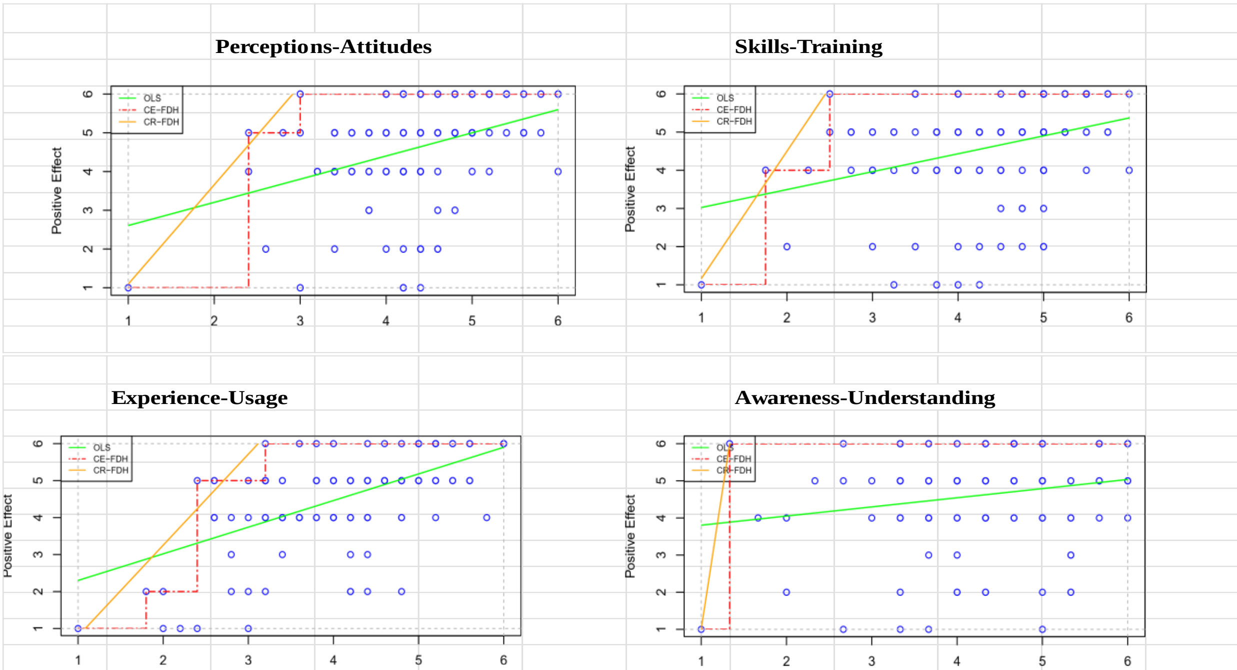

FIGURE 2
SCATTER PLOTS -FEMALE GRADS

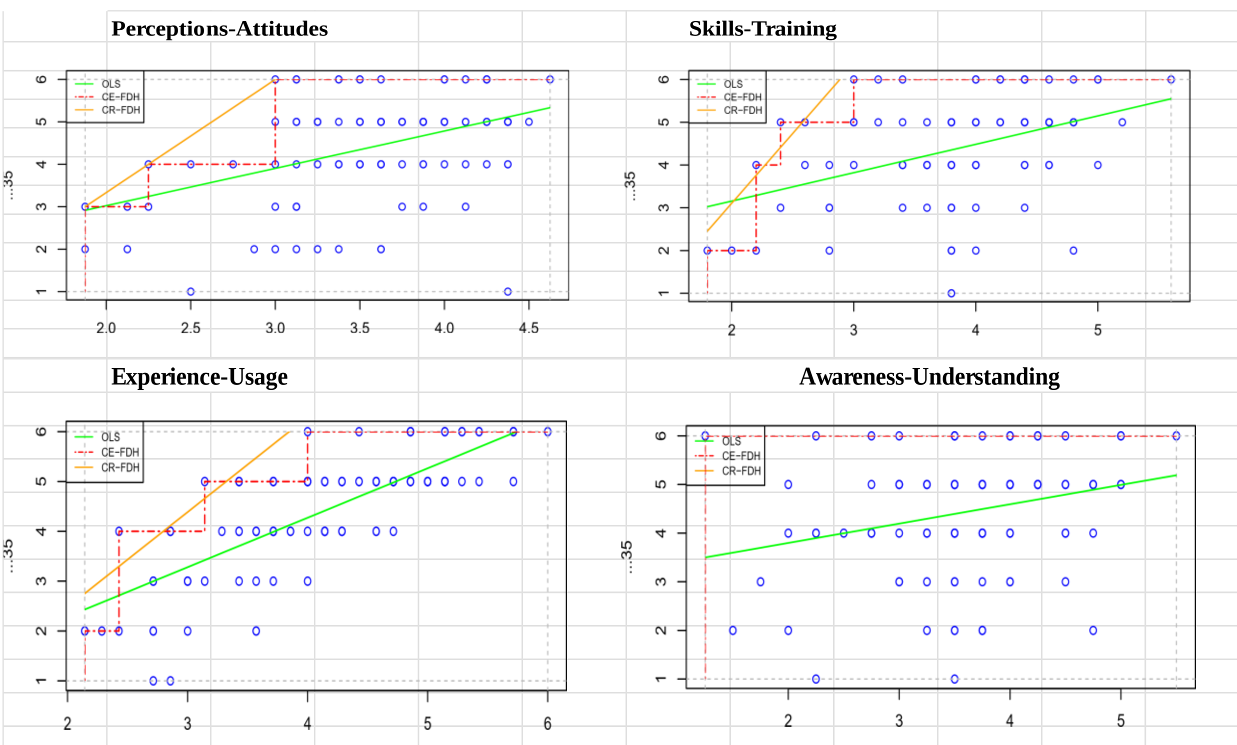

TABLE 2
NCA QUALIFIED PARAMETERS

	Perception/Attitude		Skills/Training		Experience/Usage		Awareness/Understanding	
	Male	Female	Male	Female	Male	Female	Male	Female
Ceiling Zone	4.693	1.688	3.504	1.925	5.5	2.76	0.833	0.000
Effect Size	0.188	0.123	0.140	0.101	0.220	0.143	0.033	0.000
C-Accuracy	99.40%	100%	99.40%	98.40%	97.50%	98.4%	100%	100%
Fit	61.80%	64.30%	66.70%	74.10%	76.40%	80.7%	50.00%	N/A
Slope	2.563	2.667	3.333	3.267	2.462	1.906	15	N/A
Intercept	-1.468	-2.000	-2.167	-3.427	-1.669	-1.332	-14	N/A
Abs. Ine ff.	15.614	10.375	17.992	15.147	14.422	13.752	23.333	N/A
Rel. Ine ff.	62.455	75.455	71.967	79.733	57.688	71.308	93.333	N/A
Condition Ine ff.	61.728	59.091	71	71.429	57.688	55.825	93.333	N/A
Outcome Ine ff.	1.899	40.00	3.333	29.067	0	35.050	0	N/A

Interpreting key parameters requires understanding what they represent: Ceiling zone refers virtually to the empty space above the ceiling line. Effect size refers to the magnitude of the constraint that a necessary condition (X) poses on the outcome (Y) expressed by the size of the ceiling zone relative to the size of the scope. C-accuracy refers to the extent to which cases are on or below the ceiling line expressed as a percentage of all cases. The Fit score is the effect size of a selected ceiling line divided by the effect size of the CE-FDH ceiling line. Slope and Intercept are only relevant for CR-FDH given that it is a straight regression ceiling line. The necessity inefficiency parameters indicate: (1) the area of the scope where X does not constrain Y (Condition inefficiency); (2) the area of the scope where Y is not constrained by X (Outcome inefficiency); (3) the total unconstrained area (absolute inefficiency); (4) and this area as a percentage of the scope (Relative inefficiency). For the purpose and scope of this paper we only discuss the effect size results as they are the core parameter of the NCA method. Effect size values represent the *substantive significance* of the necessity effect of X and Y. In our case, as depicted in Table 2 and across both sub-samples, the values of six out of eight effect sizes are below the threshold value of 0.5 but greater than 0.10. Thus, for either gender these results are perceived as small sizes but are deemed meaningful (Dul, 2020). And in the case of male and female grads alike, the effect size of the variable that failed this test appear to be AI-related awareness/understanding (d = 0.033 and 0.000, respectively). For the students in our sample, regardless of their gender, awareness and understanding of AI are insufficient and deemed unmeaningful for a positive learning experience.

Table 3 presents the statistical significance test *P*-value for the variables' effect size, in addition to other NCA key parameter values for both genders, respectively. Consider that we set a threshold of 0.05 for the *p*-Value. The *p*-Value test, with 10,000 permutations, suggests that the *p*-Value of the effect size of six variables – Perceptions/Attitudes, Skills/Training and Experience/Usage - are below the set threshold of ***p*** = 0.05, and thus are considered statistically significant (for male students, ***p*** = 0.017, 0.013 and 0.001, respectively; and for female students, ***p*** = 0.001, 0.008 and 0.001, respectively).

TABLE 3
KEY NCA PARAMETERS AND P-VALUE TEST

	Perception/Attitude		Skills/Training		Experience/Usage		Awareness/Understanding	
	Male	Female	Male	Female	Male	Female	Male	Female
Ceiling Zone	4.693	1.688	3.504	1.925	5.5	2.76	0.833	0.000
Effect Size	0.188	0.123	0.140	0.101	0.220	0.143	0.033	0.000
C-Accuracy	99.40%	100%	99.40%	98.40%	97.50%	98.4%	100%	100%
Slope	24.2	13.75	19.4	19	29.60	19.286	9.6	21.25
P Value	0.017	0.001	0.013	0.008	0.001	0.001	0.423	1.000

The corresponding *p*-Value of the effect size of Awareness/Understanding (***p*** = 0.423 and 1.000, respectively) is above the set threshold of *p* = 0.05, thus their effect size is statistically insignificant. In NCA terms, whereas the observed effect sizes of PA, ST and EU are not caused by random chance of unrelated variables, the observed effect size of AU could be due to random chance of unrelated variables in the case of both genders alike. Table 4 captures the essence of our findings in a summary table that allows for the formulation of a conclusion as we discuss next. Our results suggest no gender-based difference between male and female grads in our sample. Furthermore, while all four of the study's hypotheses are *theoretically* supported, the effect size of only six variables in our sample (PA, ST and EU) is less than 0.5 threshold, but larger than 0.10. And the *p*-Value of each of these six variables is less than 0.05. And since NCA requires that all three (3) criteria must be met for supporting a hypothesis, it appears that while our first second and third hypotheses are fully supported, our 4th hypothesis is unsupported.

TABLE 4
SUMMARY OF FINDINGS

	Perception/Attitude		**Skills/Training**		**Experience/Usage**		**Awareness/Understanding**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
Theoretical Support	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
d<0.5>0.10	Yes	Yes	Yes	Yes	Yes	Yes	No	No
P<0.05	Yes	Yes	Yes	Yes	Yes	Yes	No	No

In the case of male and female students in our sample, their AI-related dimensions of PA, ST and EU could be considered necessary conditions for having a positive effect on their learning experience. Their *substantive significance* (d < 0.5) and their *statistical significance* (*p* < 0.05) are strong enough to not falsify entirely the necessary condition in the study's first three hypotheses.

The bottleneck table, see Table 5 next, depicts what level of X is required for a given level of Y, and thus allows for hypothesis formulation *in degree* (in percentage range). Table 5 provides practical insight concerning the required level of the necessary conditions for a certain level of Y. The values for the variables in Table 5 are expressed in percentages. Consider that for male grads in our sample, the outcome level of a desired learning experience must be at least 10 percent; this is a fairly low level for all four conditions to 'kick in. For female grads, the level of a desired learning experience stands much higher - at least 50 percent - for the three statistically significant conditions to 'kick in.' Namely, the corresponding values for male and female grads represent the necessity level for overcoming a 'no need' (NN) level by the independent variables as a condition for achieving that outcome level. Results in Table 5 suggest that for a level of learning experience that is ≥ 40 percent for males and ≥ 60 percent for females, four double digit conditions for males and three conditions for female grads must exist in varying levels that grow with an increase in positive learning experience.

Note the negligible levels of the AI-related Awareness/Understanding condition under the male sub-sample compared with other conditions in their respective sub-sample. This very condition is entirely unnecessary (No Need) for the female grads in our study. Also consider that at 100 percent of a positive learning experience, the level of AI-related dimensions – AU, EU, ST and PA - as necessary conditions for male grads must stand at 6.7 percent, 42.3 percent, 29 percent, and 38.3 percent, respectively. For female grads, the corresponding values stand at 44.2 percent, 28.6 percent, and 40.9 percent, respectively. These findings are certainly well aligned with the results in previous tables regarding EU, ST and PA, but also highlight the relative importance of Awareness and Understanding of AI for the male grad no matter their 'light' weight.

TABLE 5
BOTTLENECKS (%)

MALE SUB-SAMPLE				
Y	1	2	3	4
0	NN	1.7	NN	NN
10	0.7	5.7	2	3.2
20	1.3	9.8	5	7.1
30	2	13.9	8	11
40	2.7	17.9	11	14.9
50	3.3	22	14	18.8
60	4	26.1	17	22.7
70	4.7	30.1	20	26.6
80	5.3	34.2	23	30.5
90	6	38.2	26	34.4
10	6.7	42.3	29	38.3

NN – No Need
Y – Learning Experience
1 – Awareness/Understanding
2 – Experience/Usage
3 – Skills/Training
4 – Perceptions/Attitude

FEMALE SUB-SAMPLE				
Y	1	2	3	4
0	NN	NN	NN	NN
10	NN	NN	NN	NN
20	NN	NN	NN	NN
30	NN	NN	0.4	NN
40	NN	3.4	4.4	NN
50	NN	10.2	8.4	6.8
60	NN	17	12.5	13.6
70	NN	23.8	16.5	20.5
80	NN	30.6	20.5	27.3
90	NN	37.4	24.5	24.1
10	NN	44.2	28.6	40.9

NN – No Need
Y – Learning Experience
1 – Awareness/Understanding
2 – Experience/Usage
3 – Skills/Training
4 – Perceptions/Attitude

DISCUSSION

The purpose of this study was to examine possible AI-related gender gaps that may exist amongst international graduate students. We used NCA for establishing necessity conditions amongst AI-related dimensions as predictors of students' positive learning experience. These dimensions included awareness and understanding of AI; experience and usage of AI; perceptions and attitudes toward AI; AI skills, education and training. Analysis of data collected from a sample of 422 Indian graduate STEM students, yielded no gender-specific differences across the four AI-related dimensions. Specifically, with the exception of the AI-related awareness-understanding dimension, which emerged as a poor predictor for both male and female students, all other AI-related dimensions emerged as statistically significant predictors of positive learning experience of students of both genders. These findings provide empirical support for three out of four of the study's hypotheses – for male and female students, respectively (H_1, H_2, and H_3) but no support has emerged for our fourth hypothesis (H_4). Specifically, AI-related skills and training ($p < .013$, and $p < .008$, respectively), perceptions and attitudes ($p < .017$, and $p < .001$, respectively), and experience and usage ($p < .001$, and $p < .001$, respectively) have emerged as significant predictors of a positive learning experience, while AI-related awareness and understanding ($p < .423$, and $p < 1.000$) emerged as a weak predictor that is deemed unnecessary for a positive learning experience. And still, AU may play a small role, nonetheless.

Our results stand contrary to much of the current research on the existing digital gender gap. Is it possible that the mere enrollment in a STEM program may attract students of both genders who a-priori possess stronger tendencies to experiment with and use innovative technology tools? Can AI be one of them? This may reduce or even eliminate gender-based differences as suggested by our findings. Moreover, given India's standing as a global IT powerhouse, it is also possible that Indian students, as a particular population group, are more technology oriented, an orientation that is shared by both genders and hence may provide additional explanation for our findings. We should further note that the study's findings appear to be in line with tenets of both theories in our theoretical framework. Consider that our results stress the value of actively engaging in self-development and self-education, particularly with regard to the use of AI.

Student’s self-experimentation and usage of the technology, as reported by our study’s participants, is remarkable given that no such training or skill-development has been offered in their graduate study programs. Thus, our results align well with the TAM model and with principles of conservatism theory, lending much credence to both approaches. Indeed, actively engaging in self-learning initiatives provide valuable insights into the benefits of using AI for learning in higher education settings. Support for the relationship between student self-learning actions and academic self-efficacy has been reported in other works (Usher, 2008; Joo et al., 2000), which in turn has been positively associated with positive student learning experience (Kryshko et al., 2022; Prifti, 2022).

As we commented in a previous paper (Authors, 2025), the emerging finding concerning AI-related awareness and understanding may not come as a surprise given that a mere understanding of a technology or being aware of its benefits may not necessarily be sufficient if a student lacks the knowledge and skills to utilize it. This argument finds some support in other research that suggests that even with a high level of awareness towards AI, students are likely to have a limited understanding of how to utilize it for learning (Ahmad et al., 2024; Kelly et al., 2023; Alimi et al., 2021; Yuzbasioglu, 2021). It is more likely that awareness and understanding of AI will serve as a first step that leads curious students to seek training, develop related skills, commence using the technology, and ultimately develop positive attitudes and perceptions toward AI. Indeed, our bottlenecks analysis encourages us not to ignore the AU dimension despite its low weight.

The inherent practical implications embedded in our findings suggest an opportunity for college administrators and faculty to zoom in on critical AI dimensions and their degree of necessity for improving and enhancing graduates’ learning experiences. In our sample of STEM program graduates, capitalizing on students’ own AI experience, usage, skills and training and on their own perceptions and attitudes toward AI, may not be sufficient per se and hence must be complemented by program directors for further nurturing graduates’ familiarity with artificial intelligence technologies, tools and applications. These should be considered as priorities for ‘in-house’ training and coaching. Mastery of AI technology by students of all academic programs constitute a priority that college administrators and faculty cannot ignore. Furthermore, we argue that a strict prohibition of artificial intelligence tools in higher education is impractical given that many students continue to use AI tools and applications in their academic studies regardless of the consequences. Admittedly, AI has made it easier for some students to cheat, but as our results suggest it is also being utilized to enhance the learning experience of students. It appears that students in our sample use AI to complement their learning process and to provide support in language learning, translation, grammar, and tutoring, thus making it a potentially valuable contribution to their learning experience. College administrators and faculty are encouraged not to underestimate such benefits when developing AI-related policies.

LIMITATIONS AND FUTURE RESEARCH

Several limitations are worth mentioning. Although fairly representative of the universe of the international student body at the targeted university (N=422), the sample reflect asymmetric gender subsamples with a tilt toward male students by a ratio of about 2 to 1. In addition, limited exclusively to Indian graduate students, the responses may not be representative of the greater international graduate student population. As significant, self-rater bias may exist given that the study’s dependent and independent variables were subjectively rated by the same participants themselves. And although at acceptable levels, the reliability scores of the instrument that was used call for caution in the interpretation of results and for further testing of the research survey with additional populations. Finally, we must keep in mind the possibility of causal indeterminacy – given that a student’s learning experience, as a dependent variable, is likely to be affected by many other unaccounted-for factors given the complex and dynamic realities of the classroom in general and of being an international learner in particular. Thus, the impossibility of determining a link to an outcome that is likely to be affected by many other factors. In addressing such limitations, we suggest future research to consider samples that include other student populations and use gender-based sub-samples that are far larger and more symmetric than the one we used.

We likewise encourage exploring other tested and more reliable survey instruments. Future research should also consider objective measures to overcome self-rater bias, along with other methodological approaches with mixed-method being one alternative. Such an approach may provide additional in-depth insights about student learning experiences. We encourage future research that further explores additional student learning experiences related links. Such research ought to also consider casual indeterminacy as a way to overcome potential limitations found in this study. Finally and in retrospect, we suggest utilizing instruments that use ranking or scenario-based responses, which have been shown to reduce response and language bias when compared to Likert-type scales (Harzing et al., 2009).

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