WIP: Examining Psychological Distance Perceptions Towards Advanced Technologies among University Students

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***Abstract*— The rapid development of advanced technologies, such as artificial intelligence (AI) and cloud computing, has led to their increasing integration into the daily lives of students, including educational settings. Yet, understanding the extent and depth of university students' engagement with these resources remains a significant gap. This work-in-progress study seeks to examine psychological distance perceptions towards advanced technologies among university students. To address this question, we created a quantitative survey guided by the Construal Level Theory (CLT) and the Technology Acceptance Model (TAM), which included two detailed psychological distance factors: the social distance factor and the hypothetical distance factor. We examined 37 university students from a Western university in the United States through linear regression analysis. We found that demographic factors, including age, race/ethnicity, and academic majors, were the primary predictors of students' psychological distance from advanced technologies. In detail, students who majored in Biomedical Engineering negatively perceived these two technologies, which could be attributed to a perceived irrelevance of these technologies to their specific educational goals. These findings provide important insights into the associations of student backgrounds and psychological distance to advanced technologies in the university setting and suggest ways to create an inclusive, equitable, and future-oriented university learning environment.**

Keywords—Psychological Distance; University Engineering Students, Advanced Technologies; Demographic Factors; Inclusive Educational Practices

I. Introduction

In engineering education, the emergence and integration of advanced technologies such as artificial intelligence (AI) and cloud computing are reshaping the required technical skills and challenging traditional teaching pedagogies. For example, AI supports complex tasks such as automatic speech recognition and language translation [1], [2], while cloud computing enables remote work through services such as data analytics and disaster recovery [3], [4]. In a certain way, these technological advancements challenge traditional pedagogies in academic environments, pushing instructors to rethink and redesign their teaching strategies to incorporate these advancements [5], [6].

Awareness of the importance of AI and cloud computing in engineering education has led to efforts to bridge the gap, ensuring all university students have equal access to these technologies. To this end, previous studies have extensively examined external obstacles, such as geographic barriers (particularly for collaborators in different time zones), policy and funding limitations, and natural environmental factors, e.g., educational resources [7], [8]. Moreover, cognitive factors and individual differences play a significant role in influencing the interest, engagement, and academic achievement of students [9]. These differences can lead to diversified approaches to advanced technology, resulting in different understandings and potentially creating obstacles to pursuing technology education and careers [10].

The concept of psychological distance helps explain how these barriers affect students' engagement with technology. This concept is defined as an individual's perceived closeness or remoteness to a subject [11], [12]. Psychological distance varies among students based on their exposure to technology. Those with less exposure may see these technologies as distant and unfamiliar, affecting their motivation and ability to engage [13]. By contrast, students with greater exposure often show more confidence and competence. Consequently, addressing both physical and psychological barriers is essential to make advanced technologies accessible and relatable for all students.

In response to these imperative needs, this study aims to characterize the psychological distance perceived by university students toward advanced technologies and to understand the reasons for having a psychological distance from advanced technology. To achieve this, the study employs two conceptual frameworks: the construal level theory and the technology acceptance model. There are two research questions for the study: 1) What is the perceived psychological distance to advanced technologies among university students? and 2) If and to which extent does the perceived psychological distance vary across students' backgrounds? By exploring these two questions, our study seeks to offer insights and actionable recommendations for mitigating psychological distance and enhancing technology integration, ultimately promoting equitable access to advanced technologies for students from diverse backgrounds.

II. Literature Review

A. Enhancing Educational Access Through Advanced Technology

Technological developments and the discussion of integrating advanced technologies into higher education settings have increasingly become prominent in recent decades in education research [14], [15]. In particular, the development of AI has nudged new approaches and dynamics in learning (e.g., personalized learning, intelligent tutoring systems, virtual collaborations), requiring instructional approaches that accommodate a diverse student population [16]. Educational technology scholars have been focused on integrating and practicing advanced technologies in classroom teachings [17], [18]. Research has highlighted significant benefits, including enhanced student motivation, improved teaching quality, and creating an inclusive and self-paced learning environment. Consequently, integrating advanced technology in higher education has led to improved educational outcomes and broadened access, providing more equitable opportunities to diverse student populations.

Integrating advanced technologies into education showcases innovation and supports inclusive educational strategies [19], [20]. This integration fosters the development of a curriculum that responds to the different needs of the students, regardless of their diverse backgrounds, so that all can benefit equally from the latest technological developments [21]. By adapting educational practices to incorporate these technologies, schools can provide more personalized and engaging learning experiences that cater to a broader range of learning styles and preferences. For example, research has shown that technology-enhanced learning environments significantly improve accessibility and self-regulated learning, leading to better educational outcomes for diverse student populations [22]. While technology has facilitated the current education, it is important to recognize that not all students have the same access to these technologies.

B. Reducing Psychological Distance to Technology among University Students

The barriers previously mentioned can lead to disparities, such as psychological distance, defined as the extent to which individuals feel distant from a concept or phenomenon [11], [23]. Psychological distance significantly impacts university students' engagement with advanced technology. Studies have shown that students who feel distant from educational technology are less likely to engage in educational activities or effectively use the technology [24], [25]. Such detachment can be categorized into various factors, including lack of previous exposure, perceived complexities of using these technologies, and feeling irrelevance to these technologies' applications to their future works [11]. Therefore, understanding and addressing the psychological distance that university students face is imperative to detect the reasons and mechanisms of their engagement with technology, particularly for underrepresented students. Studies have investigated the strategies to reduce the psychological distance gap [26], [27]. However, there is limited research that looks into the approach to reduce the psychological distance to technology in educational settings for university students with diversified backgrounds. Thus, the relationship between students' background diversity and their psychological distance towards technology is essential to enhance participation and ensure equitable access to advanced technologies.

III. Conceptual Framework

This study integrates two conceptual frameworks, construal level theory and technology acceptance model, providing comprehensive perspectives through which to examine the psychological distance to the advanced technology faced by university students in higher education settings.

A. Construal Level Theory

The construal level theory (CLT) suggests that the further an objective is from an individual in terms of time, space, social distance, or assumptions, the more abstract it becomes in their minds [12]. In this work, CLT is conceptualized and applied to examine how students perceive and relate to abstract complex technological concepts [12]. Specifically, students who perceive high psychological distance from educational technologies employed in classrooms tend to find those technologies more complex and abstract.

B. Technology Acceptance Model

Complementing the first theory, the technology acceptance model (TAM) provides a basis for understanding how perceptions of usefulness and ease of use influence students' willingness to engage with technology [28]. The model helps to characterize factors that may influence university students' acceptance and use of advanced technology tools in their education.

C. Integrating Theories

This study merges two theoretical frameworks to examine university students' psychological perceptions of advanced technology. It aims to provide insights and actionable recommendations that promote broad participation and ensure equitable access to technology for all students. Specifically, the research addresses two research questions outlined in the previous introduction section, enhancing our understanding of students' perceived psychological distances regarding advanced technology.

IV. Methods

A. Participants

The sample consisted of students from introductory undergraduate engineering classes and a graduate-level engineering class at a university in the Western region of the United States. Choosing the samples strengthens the generality of the results, as these samples provide a broad spectrum of educational stages, experiences and a handful of attended engineering majors to be investigated. Initially, the research gained 52 responses, but the final analysis dataset excluded 14 individuals who failed an attention check question, alongside one respondent removed for response acquiescence in which the participants answered all the questions identically. For detailed information about the participants, please see Table 1.

TABLE I. PARTICIPANTS' DEMOGRAPHIC INFORMATION

Demographic Variables	Groups	N
Gender		
	Men	25
	Women	9
	Prefer Not to Say	3
Age Group		
	18-19 Years Old	10
	19-20 Years Old	2
	20-21 Years Old	2
	22+ Years Old	23
Race/Ethnicity		
	Asian	17
	Hispanic/Latino	1
	White	14
	Others	4
	Prefer Not to Say	1
Standing		
	Undergraduate Students	18
	Graduate Students (Master's)	19
Major		
	System Engineering	18
	Biomedical Engineering	3
	Computer & Electrical Engineering	3
	Mechanical Engineering	8
	Others	4
Urbanicity		
	Suburban	21
	Town	2
	Urban	5
	Others	2

B. Participants Recruitment Methods

The leading author reached out to the classes' institutors directly for dissemination of the online survey to their students in the classes with either email or Canvas announcements. After completing the survey, participants entered the gift card drawing for $5 gift cards, and there was one instructor who provided extra credit as an incentive for participants to complete the survey. This research was approved by the leading author's institutional IRB.

C. Procedure

Participants completed the survey questionnaire on Qualtrics in the spring of 2024, without time and location limitations. At the beginning of the survey, participants were presented with a consent form page, which they needed to agree to participate. After gaining consent, participants answered the survey questions in a fixed order, which starts with 13 questions related to AI of social distance factor, 13 questions related to cloud computing of social distance factor, 1 attention check question, 10 questions related to AI of hypothetical distance factor, and 10 questions related to cloud computing of hypothetical distance factors. Upon completion of the first survey section, they answered the 8 demographic questions.

D. Survey Measures

Our survey instrument was developed based on CLT and TAM, providing insights into students' psychological distance to advanced technology by focusing on two specific factors: the social distance factor and the hypothetical distance factor.

In detail, the social distance factor section was composed of 26 questions that assess students' perceived ease of access to AI and cloud computing. These questions are equally distributed, with 13 questions on AI and cloud computing each. In order to provide a better sense of the questions we asked, here are two samples of the questions:

- I feel that the field of **AI** is accessible and open to people like me.
- I feel that the field of **cloud computing** is accessible and open to people like me.

We used the exact wording for AI and cloud computing questions, the only difference was the replacement of the keyword (AI and cloud computing) where we highlighted.

Then, the hypothetical distance factor questions investigated the students' level of awareness and understanding of AI and cloud computing, with a total of 20 questions, 10 questions for AI and cloud computing each. Here are the sample questions that derived from the survey:

- I feel informed about the latest developments and uses of **AI** in various fields.
- I feel informed about the latest developments and uses of **cloud computing** in various fields.

Additionally, the survey included a demographic question section, which asked about participants' information of age, gender, year(s) in school, major, household income, urbanicity, and whether they were first-generation students.

E. Data Analysis

In our study, we obtained evidence of the validity of our survey measures in CLT and TAM theoretical frameworks. Then, we conducted exploratory factor analysis (EFA) on the responses related to AI and cloud computing separately. This helped identify and eliminate items that did not contribute to the clarity or integrity of the factor structures, thereby refining our survey instrument. Through this process, we have identified and removed items that did not load adequately on their respective factors, including two questions from AI in the social distance factor, three questions from cloud computing in the social distance factor, four questions from AI in the hypothetical factor, and one question from cloud computing in the hypothetical factor. In addition, 4 participants had incomplete responses, and we adopted the method of inputting the mean of the respective questions to fill the missing values

[29]. In terms of our formal data analysis, we employed regression analysis to explore the relationships between students' perceptions of AI and cloud computing with demographic information, including factors such as age, gender, and urbanicity. To ensure a robust analysis, we conducted multiple regression analyses to assess the independent contribution of each demographic variable to differences in students' perceptions of AI and cloud computing.

V. Results

The regression analysis (see Table 2) examined how various demographic factors affected students' perceptions toward AI and cloud computing, specifically examining two factors: social and hypothetical distance factors. The analysis revealed distinct patterns and broadly indicated that demographic characteristics significantly associated or predicted with university students' psychological distance toward advanced technology. Specifically, the demographic variables of age, race/ethnicity, and majors were the three significant variables that influenced students' psychological distances. Please note that in this study, 'distance' refers to a measure of psychological alignment, where greater distances represent more positive perceptions or a stronger psychological engagement with these advanced technologies.

A. *Social Distance Towards AI and Cloud Computing*

The social distance factor measures the perceived ease of use of AI and cloud computing. The analysis shows age plays a critical role in shaping these perceptions. Younger students (18-19 years old) showed a significantly positive response to AI (see Table 2), which potentially can be interpreted as their comfort and familiarity with digital technologies from an early age or the growing environment accompanied by the development of technologies. In addition to that, participants who majored in biomedical engineering tend to have social factor influences in psychological distance to both AI and cloud computing, such results can be interpreted as a biomedical engineering major is more heavily focused on some laboratory skills in their specialty and there is a lack of integrating AI and cloud computing in their current academic learning process. Furthermore, participants who considered their race/ethnicity as Hispanic/Latino showed a more negative response to both AI and cloud computing, which potentially indicates there may exist some access barriers for Hispanic/Latino students.

B. *Hypothetical Distance Towards AI and Cloud Computing*

The hypothetical distance factor measures the perceived applicability and usefulness of AI and cloud computing. Here, ethnicity emerges as a significant factor. Specifically, Asian students have a notably more positive perception of both AI and cloud computing, which may be reflective of higher exposure to advanced technology within these communities. Conversely, Hispanic or Latino students display considerable reservations possibly due to less access to or negative experiences with these

TABLE II. Regression Analysis Results For students' psychological distance of AI and cloud computing

	Social Distance - AI	Social Distance – Cloud Computing	Hypothetical Distance - AI	Hypothetical Distance – Cloud Computing
(Intercept)	3.607*** (0.288)	4.039*** (0.243)	2.587*** (0.321)	2.451*** (0.332)
Gender				
Woman	-0.188 (0.368)	0.088 (0.311)	0.795 (0.410)	0.257 (0.552)
Age				
18-19 years old	1.101** (0.417)	0.428 (0.351)	-0.051 (0.463)	-0.344 (0.479)
19-20 years old	0.447 (0.629)	0.197 (0.531)	-1.642** (0.700)	-1.869** (0.724)
20-21 years old	0.902 (0.655)	0.110 (0.553)	-0.542 (0.729)	-0.738 (0.754)
Standing				
Undergraduate	-0.738* (0.382)	-0.303 (0.322)	0.773* (0.425)	0.842* (0.440)
First - Generation Students				
Yes	-0.262 (0.305)	0.017 (0.257)	-0.198 (0.339)	-0.080 (0.351)
Race/Ethnicity				
Asian	0.414 (0.280)	0.382 (0.236)	0.779** (0.312)	1.079*** (0.323)
Hispanic/Latino	-1.517* (0.809)	-1.205* (0.683)	-3.016** (0.901)	-2.560** (0.932)
Others	0.852* (0.445)	0.299 (0.375)	1.515** (0.495)	1.400** (0.512)
Major				
Biomedical Engineering	-1.229* (0.600)	-0.745 (0.506)	-2.243** (0.668)	-2.471*** (0.690)
Computer & Electrical Engineering	0.103 (0.339)	-0.281 (0.286)	0.208 (0.377)	-0.142 (0.390)
Mechanical Engineering	-0.415 (0.317)	0.303 (0.268)	-0.082 (0.353)	-0.421 (0.365)
Others	-0.867* (0.444)	-1.291*** (0.375)	-0.731 (0.494)	-1.276** (0.511)
Urbanicity				
Urban	0.026 (0.270)	0.131 (0.228)	0.342 (0.300)	0.434 (0.310)
Town	-0.169 (0.387)	0.175 (0.327)	-1.067** (0.431)	-0.389 (0.445)
Others	0.683 (0.709)	0.715 (0.599)	0.154 (0.789)	-0.043 (0.817)

Note: Asterisks indicate ***1%, **5%, and *10% significance levels for the p-value technologies. Then, students in Biomedical Engineering consistently show resistance towards both technologies (see Table 2), which could be due to a perceived irrelevance of these technologies to their specific educational goals. Additionally, the results show significant differences between undergraduate students and graduate students in hypothetical distance influence of psychological distance. Students with undergraduate standings tend to perceive more hypothetical distance for both AI and cloud computing. The reason for these results can be explained by undergraduate students may not have the classes that help them delve deeper into these technologies. As a result, it caused them to be less accessible or relatable.

VI. Discussion

Our study's regression analysis reveals insightful patterns in university students' psychological distances toward advanced technologies (AI and cloud computing), influenced by age, race/ethnicity, and majors. In terms of psychological distance for AI, our results indicate that younger students are more likely to see the ease of use in AI. However, it tends to diminish as students advance in their age. This decrease in social distance factors by age group can be explained from one perspective as the fast development of advanced technology is booming and younger age students are on the step of technology development, which leads to them having greater confidence in using these technologies. Meanwhile, race/ethnic differences also play a crucial role. To be specific, Asian students are generally more receptive to these two advanced technologies. On the contrary, Hispanic and Latino students have more psychological distances toward these two technologies. This situation highlights the different backgrounds students may have different situations that they may encounter in their lives that prohibit their equity access to advanced technology, it is necessary for universities to create a more inclusive environment and to get familiar with advanced technology for students from all backgrounds. This approach should go beyond simply providing access, emphasizing the importance of how technology is introduced and supported, as well as its relevance to the student's cultural backgrounds in terms of age or generation, race/ethnicity, and attended major.

In addition, there appears to be a limited adoption of cloud computing within certain academic fields, such as Biomedical Engineering, which may reflect the field's focus on lab-based work rather than a direct reliance or integration of AI and cloud computing technologies into their teaching settings. This observation suggests a divergence between the existing technological applications and these lab-based work disciplines' specific educational and professional needs. Such a divergence presents a reality that the National Science Foundation (NSF) recognized the potential issues of the separation of advanced technologies in these lab-based work fields, and in recent years NSF provided more funding to help the integration of advanced technologies into these fields [30].

VII. Limitations and Future Directions

While our findings offer valuable preliminary data insight, this study has several limitations that must be acknowledged. First, the study's sample size is only 37 participants, and in particular, there is only one Hispanic/Latino participant and no African American/Black participants which restricted our ability to observe robust and generalizable results, providing statistically meaningful explanations. This limitation can be solved in the future as more participants will be recruited for this study, and in the future full paper we will go from there to see whether the perceptions of psychological distances will be changed based on a large sample. In addition to the limitation of sample size, we think the study could potentially benefit by implementing qualitative methods such as interviews or focus groups to explain the quantitative results. By using qualitative methods, it can potentially provide the deeper reasons and logistics behind the numerical results about how university students have such psychological distances to these advanced technologies.

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