Mapping Favorability and Concern in Undergraduate Attitudes Toward Artificial Intelligence

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***Abstract*—As AI tools become more prevalent in both academic and everyday contexts, it is crucial to gain insight into students' perceptions of AI. This paper presents a secondary analysis of a public survey dataset comprising 460 undergraduate students from five universities in Ho Chi Minh City, Vietnam. The research focuses on the extent of use of AI, the most common purposes of use, and the attitude pattern from favorable and concern-oriented questionnaire items. To analyze data, descriptive statistics, reliability analysis, and ordinary least squares regression were used. The data indicates a high level of familiarity with AI, with 96.5% of respondents having used AI tools before. Learning appeared as the most frequently used, followed by working, entertainment and translation. The overall mean score was 3.26/5, with the favorable-attitude subscale at 3.43/5 and the reverse-coded concern subscale at 3.01/5. The results show a moderate yet skeptical attitude towards AI among the undergraduate students. The regression analysis also revealed that the age was negatively correlated with the overall attitude while year of study was positively correlated with the overall attitude, but with a low model explained variance. Overall, the results indicate that undergraduate perspectives on AI are a mix of hope and worry, underscoring the need for greater awareness, criticality, and responsibility around AI interactions in the university setting.**

Keywords—artificial intelligence, undergraduate students, higher education, attitudes toward AI, survey analysis, educational technology.

I. Introduction

Artificial Intelligence (AI) in higher education has been increasingly making its mark in the fields of intelligent tutoring, automated assessment, adaptive support, learning analytics, and generative tools [1]. An AI systematic review in higher education revealed that there was a high concentration of AI applications for profiling, prediction, assessment, and tutoring [2]. AI's role in education has also been expressed in the terms of AI-directed education, AI-supported education, and AI-empowered education [3]. AI emerged as a transformative force in education as part of the Beijing Consensus. Later, UNESCO's policy guidance highlighted the need for the human-centered and equitable adoption of AI in the education system [5]. UNESCO has also recommended ethical governance, transparency, accountability and human oversight in its recommendation on the ethics of AI [6]. Recent guidance about generative AI focuses on responsible use, critical evaluation and institutional safeguards [7]. The AI competency framework for students further reinforces student agency and informed participation in AI-enabled environments [8].

AI literacy is not just about knowing how to use tools, but also understanding the underlying principles and concepts. It includes understanding, assessing and interacting with AI systems in an appropriate way [9]. In the past, researchers studying AI literacy had been more focused on conceptual understanding and critical engagement, as revealed in a systematic review of the literature [10]. Knowledge, skills, attitudes, and ethical awareness are also mentioned as key elements of AI competence in a broader competency framework [11]. Alongside, attitude research indicates that attitudes towards AI are not monochromatic. Initial validation of the General Attitudes toward Artificial Intelligence Scale showed the existence of both positive and negative attitudes [12]. This two factor interpretation was confirmed by subsequent work [13]. Reliability generalization studies further confirmed the continuing usefulness of such measures [14]. AI anxiety has been found to influence the attitudes held towards AI in the educational environment [15]. The fears associated with AI dimensions have also been reported [16]. Other factors, such as personality and demographics, also predict attitudes toward AI [17]. The same evidence has been observed for more general personality factors that predict AI acceptance [18].

Higher education studies over the last few years have revealed that students seem to believe that AI can be helpful for writing, learning assistance, productivity, and brainstorming [19]. Research into large-language-models has also pointed to the significant educational opportunities as well as risks [20]. Education research on ChatGPT also exhibits promise and concern.There is also research on education related to ChatGPT, which exhibits promise as well as concern [21]. The implications of generative conversational AI for research, practice and policy have received a multidisciplinary focus [22]. Other management education scholars have also called generative AI an 'enabling and disruptive technology' [23]. Empirical studies also indicate that students are using chatbots in assessment situations, leading to academic integrity concerns [24]. The cross-country work also shows that there are sometimes differences between what students and educators think about generative AI [25]. The attitude modelling studies also validate that cognitive, affective and behavioral components all influence student reactions to ChatGPT [26]. Other research indicates that students are quite useful with generative AI even when they are not very confident on its reliability [27]. Recent research on learning with GenAI further indicates that technology, ethics, social issues and the individual play a role [28].

The reality is that context continues to be significant, as is confirmed by research from the regions. Across India, there are indications of active institutional involvement in the process of adopting AI in higher education [29]. University students in Slovenia had generally good but qualified attitudes towards AI tools, according to an AI study [30]. AI attitudes among students have also been identified as being significantly different across countries in international comparative studies [31]. Survey data across nations also align with the benefits of studying AI literacy, readiness, anxiety, and intention in tandem [32]. In Vietnam, previous studies reveal that the attitudes of undergraduate students are somewhat positive towards AI, while AI is still relatively underdeveloped in Vietnam [33]. Against this backdrop, this study investigates undergraduate attitudes regarding AI with the help of a concise analytical framework that integrates student background information, AI usage, purposes of AI usage and attitude measures of both sides (favorable as well as concern-based).

II. Literature Survey

The application of AI in higher education has been explored in instructional, administrative and learner-support roles [1]. According to the review of research, the most prevalent areas of application are predictive analytics, intelligent tutoring, profiling, and assessment [2]. In the context of the three paradigms of AI-directed, AI-supported, and AI-empowered education, it can be better understood how AI impacts the relationship between automation and human agency in education [3]. The global policy documents have also placed AI as an opportunity for inclusion and quality improvement [4]. There has been a focus on careful implementation, not uncontrolled adoption, in educational systems [5]. Transparency, accountability, privacy, and human oversight have also been highlighted as key ethical considerations [6]. These concerns have further been extended to teaching, learning and research with recent guidance on generative AI [7]. Current student competency models have shifted focus to emphasizing the development of skills related to AI's role in responsibility, critical thinking, and participatory understanding [8].

A general consensus in the literature on the term AI literacy, which is defined as the ability to interact with, communicate with, interpret, and understand AI [9]. AI literacy in educational settings reveals that it involves more than just technical knowledge—it also encompasses ethical considerations, critical analysis, and an understanding of its applications [10]. Similarly, in a more recent competency synthesis, knowledge, skills, attitudes and values are described as interconnected elements of AI learning [11]. The GAAIS framework identified the following AI attitudes from an attitudinal perspective: positive and negative aspects [12]. Subsequent validation studies confirmed the stability of this structure and their relationship to broader trust dispositions [13]. These attitude measures are found to be reliable for different types of studies [14]. Concurrently, the phenomenon of 'AI anxiety' has become a significant explanatory framework for studying student behaviors in education [15]. Also, the dimensions of fear are empirically separated from the dimensions of danger, loss of control and uncertainty [16]. AI attitudes are also moderated by personality traits and demographics [17]. Similar findings in personality psychology studies have also revealed that openness and associated traits can impact the way that people perceive AI [18].

The research into student perceptions in higher education has been speeded up by Generative AI. Writing support, study assistance, and idea development are seen as strong perceived benefits of student-centered work reports [19]. Similarly, the large-language-model scholarship has viewed these advantages as counterbalanced by issues of accuracy, dependency, and classroom redesign [20]. The research on chatbots also focuses on the conflict between use and abuse [21]. A wider range of multidisciplinary views have identified the need for governance and policy adaptation [22]. This moment has been called disruptive and reformative in the perspectives of management education [23]. The examples of assessment contexts provide empirical evidence that students' chatbot usage pose integrity-related questions [24]. Research on comparative sentiment of generative AI in assessment has revealed differences in sentiment among groups of stakeholders [25]. The findings from path-analysis studies also underscore the cognitive, affective, and behavioral aspects of student perceptions in relation to ChatGPT [26]. Further evidence reveals that students frequently feel generative AI is beneficial, but believe that it is not entirely accurate [27]. Recent acceptance-based research has validated the importance of ethical and social issues in the context of GenAI-integrated learning [28].

AI attitudes are influenced by institutional and cultural context, as observed in region-based studies. Evidence from higher education in India indicates a trend towards increased use but varied perceptions between settings [29]. Similarly, in Slovenia, students are interested in AI tools but also have some practical issues regarding their use [30]. Comparative studies of students from across the globe also show that attitudes are not consistent across nations [31]. Similarly, cross-national survey datasets also reveal correlations between levels of AI literacy, readiness, anxiety, and intention to use AI across populations [32]. In Vietnam, previous studies show a relatively positive attitude among students towards AI integration, though there is a lack of comprehensive studies in this field [33]. The present study therefore fills a specific gap in the literature by examining the elements of AI exposure, concrete aims of AI utilization and attitude measures in a combined fashion.

III. Methodology

A. Dataset and Survey Instrument

This study performs a secondary analysis of the public dataset released by Le [34], which is linked to the related Vietnam study reported in [33]. The data used is based on the responses from 460 students in five universities who were studying under graduation. The survey instrument consists of two large sections: The first one collects information about the background of the participants and information about their use of AI, including their university, gender, year of study, age, field of study, prior AI usage and reasons for AI use. The second section assesses attitudes towards the use of AI with 20 statements rated on a 5-point likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Items 1-12 indicate positive perceptions of AI, while Items 13-20 indicate concern-oriented perceptions related to error, risk, unethical use, and surveillance. Fig. 1 shows the statement-level favorability profile across the attitude items, highlighting which questionnaire statements received the highest and lowest levels of favorable response among undergraduate students.

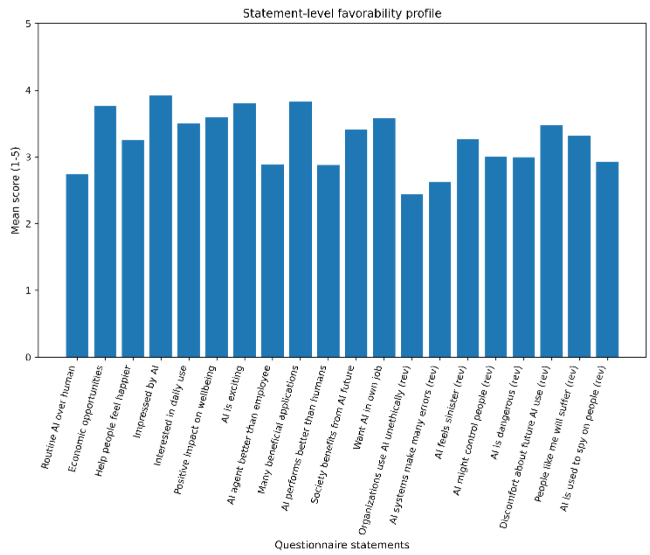

Fig. 1. Statement-level Favorability Profile

A small modular structure was followed to structure the study workflow. This framework has five stages: Input, Usage, Scoring, Analysis and Output. Questions are asked in the input stage to gather demographic and academic factors. The usage stage reflects previous exposure to AI and the primary purposes of AI usage. At the scoring stage favorable, concern-oriented, reverse coded, and overall attitude indices are calculated. At the analysis stage, the reliability test, descriptive analysis, group comparison and regression modelling are used. Finally, the output stage summarises the usage patterns, the most important predictors and the empirical findings. Fig. 2 shows the proposed analytical framework of the study, including the progression from participant inputs and AI-use information to scoring, statistical analysis, and final findings.

Fig. 2. Proposed Analytical Framework

B. Data Preparation and Variable Construction

The data was preprocessed before data analysis. Demographic variables were used to decode their terms into meaningful categories and the multiple-response AI-purpose fields were converted into a binary variable for learning, entertainment, working, health care, translation, and other purposes. Moreover, a variable was created to indicate the number of different uses of AI that each participant reported, which is called a purpose-count variable.

The scoring of the favorable and concern-oriented indices were recalculated from the raw questionnaire items to ensure consistency of scoring. The favorable-attitude score was the average of the 12 items on the score sheet while the concern-oriented score was the average of 13-20. The final score for overall attitude was computed using the concern oriented items, which were reverse coded, to eliminate the effect of higher concern scores being not necessarily better attitudes. The scores on the overall attitude variable thus reflect a more positive attitude toward AI. Fig. 3 shows the main purposes for which undergraduate students reported using AI, based on the multiple-response survey item covering learning, entertainment, working, health care, translation, and other uses.

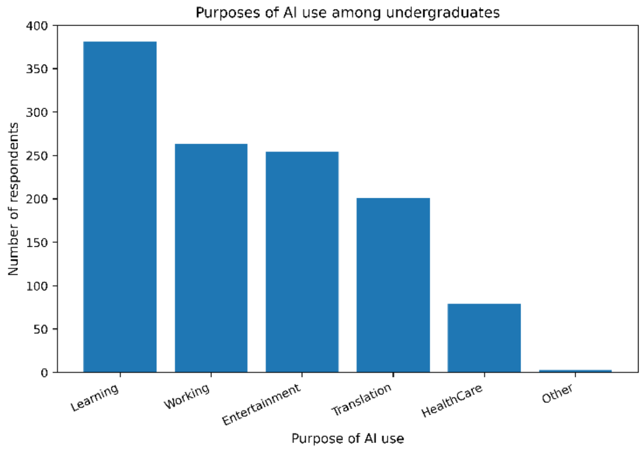

Fig. 3. Purposes of AI Use Among Undergratuates

The following scoring procedure was used:

$$\text{Positive Score} = \frac{1}{12}\sum_{i=1}^{12} x_i$$

$$\text{Negative Score} = \frac{1}{8}\sum_{i=13}^{20} x_i$$

$$\text{Negative Reversed} = \frac{1}{8}\sum_{i=13}^{20} (6 - x_i)$$

$$\text{Overall Attitude} = \frac{1}{20}\left(\sum_{i=1}^{12} x_i + \sum_{i=13}^{20} (6 - x_i)\right)$$

This scoring design preserves the original two-sided nature of the instrument while enabling a unified interpretation of the final attitude index.

C. Statistical Analysis

Standard data-analysis and statistical libraries were used to perform the analysis in Python. Cronbach's alpha was used to assess internal consistency. Participant characteristics, AI-use behavior, and attitude scores were summarized using descriptive statistics. Next, an independent-samples t-test was conducted to investigate differences in overall attitude between the groups with and without AI use.

Overall attitude was used as the dependent variable and an ordinary least squares (OLS) regression model was fitted to investigate the predictors of AI attitude. The predictor set consisted of the followings: age, year of study, prior use of AI, and the major AI-use-purpose indicators. The ‘other’ use-purpose category was not substantively interpreted as it was only marked by a very small number of respondents.

IV. Results and Analysis

A total of 460 undergraduate students were used in the final sample. The institutional representation was fairly even with one university responding with 100 respondents and the other four each responding with 90. The larger proportion of the sample (264) was female and 196 was male. Academic stage wise, the biggest group were sophomore students (186), followed by juniors (118), freshmen (92) and seniors (64). The average age of the respondents was 19.64 years.

The use of prior AI was very common in the sample. Of all the students, 444 said that they used AI tools before, and 16 students said that they never used AI. This distribution indicates that there is already widespread exposure of undergraduate students to AI.

The purpose-of-use analysis also indicates that the primary uses of AI are for academic and productivity related purposes. The top use for AI was for learning, followed by work, entertainment, and translation. Use for health care was the least frequent and "other" was insignificant. The results indicate that AI is seen primarily as a practical tool and not as a specialized or niche technology.

The reliability analysis indicated acceptable internal consistency for the favorable-attitude scale, and borderline but usable internal consistency for the concern-oriented and overall scales. In particular, Cronbach's alpha for the favorable-attitude items was 0.748, for the concern-oriented items it was 0.695, and for the overall scale (reversed items) it was 0.674. The values suggest the instrument is good for exploratory attitudinal analysis. Fig. 4 shows the comparison between favorable attitude scores, reverse-coded concern scores, and overall attitude scores, with 95% confidence intervals indicating the relative balance between optimism and caution toward AI.

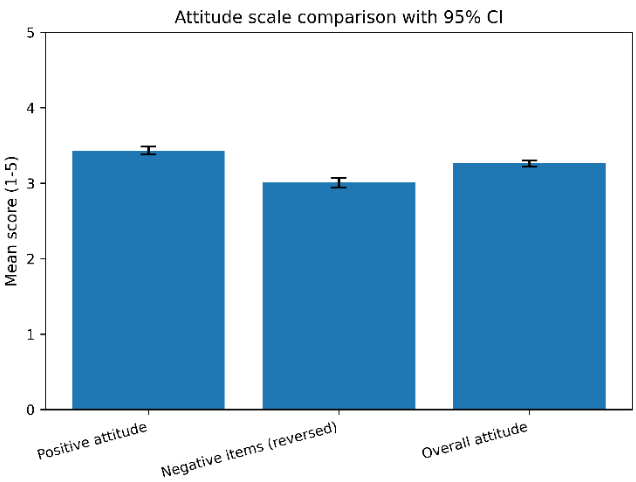

Fig. 4. Attitude Scale Comparison with 95% CI

The descriptive results show a rather positive overall attitude towards AI. The favorable-attitude score had a mean of 3.43, while the concern score (which was reverse-coded) had a mean of 3.01 resulting in an overall attitude mean of 3.26 on a five-point scale. This pattern suggests that students have rather positive, but not uncritical, attitudes toward AI. Rather they answer with a combination of excitement and skepticism.

The most positive responses were linked to being impressed with AI, finding it exciting and understanding the positive uses and economic opportunities of AI at the statement level. In contrast, there was a relative lack of favorability for using AI rather than people in routine transactions, and for the reverse-coded concern statements about future uses, social harms, and surveillance. As emphasized by this item-level pattern, the attitude of undergraduates is effected by optimism and apprehension.

To compare the overall attitude of the students with the students who have not used AI, an independent-samples t-test was performed. This was not a statistically significant result ($t=-0.338$, $p=0.73984$), suggesting that there was no meaningful difference in overall attitude in this sample based on the participants' prior AI-use status. This result must be taken with a pinch of salt, however, as the number of non-users was small compared to that of the users. The implication in practical terms is that after a certain degree of diffusion, the effect of simply being exposed to AI may not be strong enough to differentiate attitudes.

To explore AI attitude further, an OLS regression model was estimated and the attitude towards AI was the dependent variable. The model was statistically significant overall ($F=2.900, p=0.00240$), however only had a modest explanatory power ($R^2=0.055$). The results suggest that only a portion of the variance in student attitudes toward AI is explained by the predictors included. Of the predictors, age was significantly negatively correlated with overall attitude ($b=-0.154$, $p<0.001$), and year of study, significantly positively correlated ($b=0.159$, $p<0.001$). However, the use of AI before the survey and the various reasons for using AI were not found to be statistically significant in the final model. These findings indicate that perceptions of AI may relate more with academic stage than with just being a user or not. The simultaneous analysis of age and year of study needs to be viewed with caution as these are conceptually linked. Fig. 5 shows the OLS regression coefficients for the predictors of overall attitude toward AI, together with confidence intervals that indicate the direction and strength of each predictor's effect.

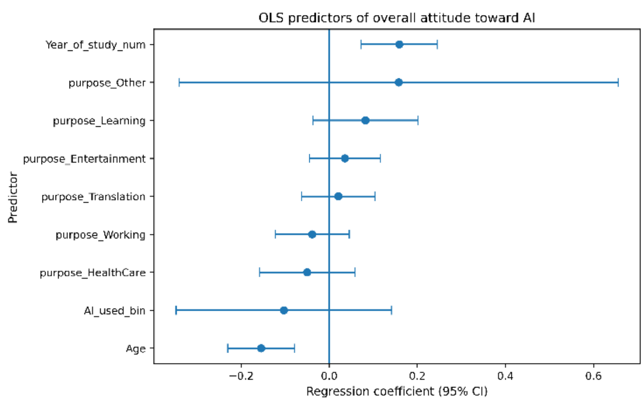

Fig. 5. OLS Predictors of Overall Attitude towards AI

The direction and uncertainty of regression estimates were visualised using a coefficient Plot. The plot is clearly showing that age and year of study are the only variables that showed confidence intervals that did not significantly cross zero, the other variables showing weak and unstable effects.

TABLE I. SUMMARY OF KEY DESCRIPTIVE, RELIABILITY, AND INFERENTIAL RESULTS

Category	Metric	Value
Sample	Number of respondents	460
Sample	Mean age (SD)	19.64 (1.10)
Sample	Female	264 (57.4%)
Sample	Prior AI use	444 (96.5%)
AI use*	Learning	381
AI use*	Working	263
AI use*	Entertainment	254
AI use*	Translation	201
Reliability	Positive attitude, α	0.748
Reliability	Concern-oriented items, α	0.695
Reliability	Overall attitude, α	0.674
Attitudes	Positive mean (SD)	3.43 (0.58)
Attitudes	Reverse-coded concern mean (SD)	3.01 (0.68)
Attitudes	Overall attitude mean (SD)	3.26 (0.43)
t-test	AI users vs. non-users	$t = -0.338$, $p = 0.740$
OLS	Age	$B = -0.154$, $p < 0.001$
OLS	Year of study	$B = 0.159$, $p < 0.001$
OLS	Model fit	$F = 2.900$, $p = 0.002$, $R^2 = 0.055$

*Multiple responses allowed.

V. DISCUSSION

The results have shown that AI is already an important part of the academic and real-world experience of undergraduate students. This uptake of AI is very high, indicating that it is not an emerging or new phenomenon among this population. Rather it has become a part of normal student's life, particularly for learning, working and translation related activities. This reinforces the idea that AI is no longer a new technology to be explored, but a tool that should be embraced as part of the educational process.

Meanwhile, the attitude results do not indicate uncritical acceptance. Moderately positive attitudes in the overall picture, however, the items relating to concern show a cautious attitude. The students aren't against AI, they're not for it either. This is significant because it indicates that undergraduate attitudes toward AI are not monodimensional, or polarized, but rather are mixed between positive and negative. Students might appreciate the role and capabilities of AI but have questions regarding ethics, future implications, and surveillance worries.

The results are inferential, adding another layer of nuance. Although some differences were found for attitudes, no significant difference was found between the attitudes of those who were and were not using AI in their design work, presumably due to the fact that the majority of the sample were already using AI. In contrast, the overall model accounted for a modest amount of variance, and only age and year of study were significant predictors. An explanation is that academic maturity influences the perception of AI more than being just exposed to it. While chronological age doesn't necessarily translate to higher optimism, some students' view of AI might be more purposeful if they have more advanced academic experience.

In the educational context, this means that higher education institutions need to shift from the mere exposure to AI to the emphasis on education for AI literacy. Students are already accustomed to using AI extensively, so the challenge now is to guide them through its evaluation, error recognition and analysis, ethical implications, and responsible usage. Overall, the research underscores the importance of adapting AI tools and strategies to maintain a balance between practical application and critical thinking.

There are some limitations of this study. The first is that it is a secondary analysis of a public data set, and thus relies on the variables included in the initial survey design. Secondly, the information is self-reports and the data are cross-sectional, limiting the ability to interpret causality. Third, there were very few non-users, limiting the power of the comparisons across groups by AI-use status. Lastly, the relatively small R^2 value suggests that other factors of interest, such as trust, AI literacy, digital competence, disciplinary culture or academic performance, were not included in the present model.

VI. CONCLUSION AND FUTUREWORK

This paper carried out a secondary analysis of the undergraduate attitudes towards artificial intelligence based on the survey-based framework which combines the student background, the behavior of use of artificial intelligence, the attitudes scoring and the inferential analysis. The results indicated that the level of AI use among undergraduate students was high, and learning was the predominant purpose of AI use. The attitude results reflect a moderately positive overall attitude towards AI, with a clear underlying ethical, error, risk, and future concerns remaining.

The inferential results indicated that age and year of study were the only significant variables for overall AI attitude, while the other variables (prior AI-use status and specific use purposes) were not significant in the final model. The findings indicate that the attitudes towards AI in higher education are not solely determined by the direct experience of using AI, but also by the surrounding environment or context in which such use occurs.

This study can be extended further in the following directions: A direction is to integrate variables that are associated with AI literacy, trust, perceived usefulness, and academic dependency. The other is to make an inter- or intra-disciplinary comparison between attitude patterns. Next, it would be beneficial to perform longitudinal or intervention studies to investigate the impact of education programs on the relationship between optimism and concern about AI. The report will offer valuable insights to design more informed and responsible approaches in the integration of AI in higher education institutions.The report will provide valuable insights to design more informed and responsible approaches in the integration of AI in higher education institutions.

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