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# The Impact of Career Anxiety, Dehumanization, and Perceived Algorithmic Fairness on AI Anxiety among Indonesian University Students: A PLS-SEM Study

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**ABSTRACT**

The rapid integration of artificial intelligence (AI) in higher education has raised concerns about students' psychological readiness, particularly regarding AI Anxiety. This study examines the influence of Career Anxiety, Dehumanization, and Perceived Algorithmic Fairness on AI Anxiety among Indonesian university students. Using an explanatory survey design, data were collected from 70 students who actively use AI-based learning tools. The analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess the measurement and structural models. The results show that Career Anxiety positively affects AI Anxiety ($\beta = 0.234$, $t = 1.691$), while Dehumanization emerges as the strongest predictor ($\beta = 0.415$, $t = 2.958$). In contrast, Perceived Algorithmic Fairness has no significant effect ($\beta = 0.103$, $t = 0.740$). The model explains a substantial portion of variance in AI Anxiety with an $R^2$ value of 0.482. These findings highlight that emotional and identity-related factors are more influential than evaluative perceptions of fairness in shaping AI Anxiety. The study emphasizes the need for human-centered AI integration, improved AI literacy, and targeted support to mitigate student anxiety in AI-supported learning environments.



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## INTRODUCTION

The rapid development of artificial intelligence (AI) has given rise to a new psychological phenomenon known as *AI Anxiety*, which is a sense of unease about the social and ethical implications of this technology [1]. The McKinsey report states that millions of workers will have to change professions due to automation, thereby increasing concerns about the future of technology [3]. This condition reflects that anxiety about AI is not merely a technical issue, but also an emotional and social issue for the younger generation. Therefore, a deep understanding of AI Anxiety is becoming increasingly important in the context of higher education.

In Indonesia, the use of AI in education is growing rapidly through the Making Indonesia 4.0 program and campus digitization [4]. Although AI is considered capable of improving learning effectiveness, students still feel uncertain about the accuracy, bias, and impact of technology on critical thinking skills [5]. Limitations in AI literacy, ethical regulations, and data protection policies further exacerbate these concerns [6]. As a result, technology that should support learning has instead raised concerns about system fairness and the potential loss of human control. This situation highlights the imbalance between the potential of technology and students' psychological readiness.

Socio-Technical Systems Theory (STST) was used in this study to explain the relationship between technology and social systems in educational environments. This theory emphasizes that an imbalance between technical and social aspects can cause psychological stress such as anxiety or resistance [7]. In the context of AI, this pressure arises when students feel threatened in their careers or lose their humanity during the learning process [8]. Previous research has also shown that the dominance of technology without considering social factors can reinforce perceptions of threats to the role of humans in modern education [9]. Thus, STST provides a strong theoretical basis for understanding how psychosocial variables contribute to AI Anxiety.

Previous research on AIED has shown that there are two sides to the use of AI: increased efficiency and the emergence of complex ethical issues [10]. Common challenges include a lack of transparency, algorithmic bias, and the risk of dehumanization in learning interactions. In addition, the level of user trust in AI greatly influences how they assess its reliability and security [11]. Other studies indicate that AIED research still focuses more on technical aspects than on the psychological impact on students [12]. Therefore, a more comprehensive literature synthesis is needed to understand AI from a social-emotional perspective.

Although many studies discuss the implementation of AI in education, empirical research on AI anxiety remains limited and has not comprehensively integrated socio-emotional factors [12]. Previous studies have tended to emphasize the technical aspects of AIED, so that the relationship between career threats, dehumanization, and perceptions of algorithmic fairness toward AI anxiety has not been systematically tested [10]. In addition, research on the psychological perceptions of AI users still produces inconsistent findings, especially regarding how moral and fairness factors trigger technological anxiety [11]. The Indonesian context has also not been widely researched, even though the use of AI in education is increasing and eliciting new emotional responses among students [5]. Thus, there is an urgent need for research that specifically analyzes AI Anxiety through the Socio-Technical Systems Theory framework so that this gap can be filled.

Theoretically, this study contributes by expanding the application of STST to explain how the imbalance between technology and students' social needs can trigger AI Anxiety. This approach provides space to understand variables such as career threats, perceptions of dehumanization, and algorithmic fairness as part of socio-technical dynamics. Practically, this research can serve as a basis for educational institutions in designing ethical and psychological strategies to reduce student anxiety related to AI. The research findings can also support national policies in developing more humane and sustainable digital learning. Thus, this study contributes directly to efforts to create a balanced and ethical AI-based education ecosystem.

This study aims to analyze the influence of *Career Anxiety*, *dehumanization*, and *Perceived Algorithmic Fairness* on AI Anxiety among students. This objective stems from the need to understand the relationship between technical and psychological factors in AI-based educational environments. Theoretically, this study expands the application of STST in analyzing the dynamics of technological anxiety among students. Practically, this study provides a basis for educational institutions in designing more humane and ethical AI-based policies and learning. Through this approach, this study is expected to contribute to the development of a learning system that balances technological innovation and the psychological well-being of students.

Based on the research gap described in the introduction, the research questions posed in this study are as follows:

1. How does *Career Anxiety* affect *AI Anxiety* among students in the context of using artificial intelligence technology in learning?
2. How does *dehumanization* influence the level of *AI Anxiety* experienced by students when interacting with AI-based learning systems?

3. How does *Perceived Algorithmic Fairness* affect students' *AI Anxiety* in learning processes involving artificial intelligence technology?

These questions form the basis for the research analysis framework and will be used to explain the empirical relationship between variables in the context of AI-based higher education.

## METHOD

### Research Design

This study uses a quantitative approach with an explanatory survey method to examine the relationship between variables in a measurable manner. The quantitative approach was chosen because it allows researchers to test hypotheses through objective numerical analysis, as explained in the description that quantitative research emphasizes the process of measurement and statistical analysis [13]. The design choices also follow the characteristics of explanatory research, which requires the formulation of causal relationships in a structured manner so that the data collection process is consistent with the research objectives [14]. In addition, an explanatory survey was used because this study aims to explain the influence of three independent variables *Career Anxiety, Dehumanization, and Perceived Algorithmic Fairness* on the dependent variable *AI Anxiety* in the context of higher education. Student interaction with AI technology in learning is also an important basis because their perceptions of AI influence their learning experiences, as explained that student preferences can affect how they interpret technology [15]. Therefore, the explanatory survey method is considered the most appropriate for systematically examining the relationship and influence between these variables through the distribution of questionnaires.

### Participant

This study involved college students who have used or interacted with AI technology in their daily learning processes. The use of AI-based technology in higher education continues to grow, especially through digital platforms and learning support systems that are now a regular part of the learning ecosystem [12]. In addition, academic chatbots such as ChatGPT are beginning to play an important role in helping students obtain explanations, guidance, and corrections quickly, as has been shown in previous studies [16]. The selection of students as participants is also in line with the principle of determining the domain of study in explanatory research, which emphasizes the importance of matching the characteristics of the population with the phenomenon being studied [14]. Examples of technologies used include ChatGPT, Gemini, AI writing applications, learning recommendation systems, and AI-integrated digital platforms.

### Population and the methods of sampling

The population in this study consists of college students who have used artificial intelligence (AI)-based technology in their learning activities. The use of AI in the context of higher education is becoming increasingly widespread and is part of the modern digital learning ecosystem [12]. Students are not only passive users, but also actively involved in interactions through adaptive learning platforms, AI-based writing applications, and academic chatbots that support the learning process [15]. The sampling technique used was purposive sampling, with the criterion that respondents must have real experience in using AI technology during the learning process. This approach was chosen to ensure compatibility between the characteristics of the subjects and the phenomenon being studied. The sample size in this study followed the PLS-SEM rule of thumb, namely the 10 times rule, where the sample size is determined based on the largest number of indicators in a construct or the number of free paths leading to a variable [17]. Thus, the sample size obtained is expected to meet the standards of feasibility for PLS-SEM model analysis and estimation.

**Instrument**

This study uses a questionnaire as the main instrument to collect data related to Career Anxiety, Dehumanization, Perceived Algorithmic Fairness, and AI Anxiety among college students. The questionnaire was designed using a 4-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = agree, 4 = strongly agree) to measure the respondents' level of agreement with each statement [18]. A 4-point scale was deliberately chosen without a neutral option, thereby encouraging respondents to provide clear answers and reducing the possibility of hesitant responses. This approach is appropriate for the characteristics of the target population, as it simplifies the questionnaire completion process while maintaining the reliability and validity of the data obtained.

**Table 1.** Aspects and Descriptive Items

| Constructs | Items Code | Item Description |
|---|---|---|
| **Career Anxiety** | CA1 | I feel pressure from my surroundings to adapt to developments in Artificial Intelligence (AI). |
| | CA2 | I am concerned that the integration of Artificial Intelligence (AI) in various fields of work may reduce the career opportunities I am preparing for. |
| | CA3 | I feel anxious when I think about my future career amid the development of Artificial Intelligence (AI). |
| **Dehumanization** | D1 | I feel that the use of Artificial Intelligence (AI) in learning makes me appear incapable of thinking independently. |
| | D2 | I feel that Artificial Intelligence (AI) does not appreciate the uniqueness of my learning style as an individual. |
| | D3 | I feel that my interactions with Artificial Intelligence (AI) emphasize the end result more than the learning process I am undergoing. |
| **Perceived Algorithmic Fairness** | PAF1 | I feel that my interactions with Artificial Intelligence (AI) emphasize the end result more than the learning process I am undergoing. |
| | PAF2 | I feel that Artificial Intelligence (AI) decisions provide consistent results for every student. |
| | PAF3 | I feel that the Artificial Intelligence (AI) system continues to respect the differences in learning styles and personal contexts of students in the learning process. |
| | PAF4 | Overall, I consider the use of Artificial Intelligence (AI) in learning to be reasonable and rational. |
| **AI Anxiety** | AA1 | I often feel anxious when I have to use Artificial Intelligence (AI) to complete my college assignments. |
| | AA2 | I am concerned because I do not clearly understand how Artificial Intelligence (AI) processes information to generate decisions. |
| | AA3 | I feel that the development of Artificial Intelligence (AI) has the potential to reduce the career opportunities I am preparing for. |
| | AA4 | I feel uncertain about the social and ethical implications of using Artificial Intelligence (AI), which makes me anxious. |

The questionnaire in this study was developed by adapting instruments that had been used in previous studies and adjusted to the context of Artificial Intelligence in Education (AIED). The Career Anxiety variable was adapted from [19], which measures students' anxiety related to self-preparedness, social pressure, economic concerns, and emotional responses to career prospects amid the development of AI. Furthermore, the Dehumanization variable refers to [20], which focuses on students' perceptions that interaction with AI can reduce personal value, autonomy, and emotional aspects in the learning process. The Perceived Algorithmic Fairness variable is adapted from [21], which evaluates the extent to which students assess the fairness of information, the fairness of the process, and the overall fairness of decisions made by AI systems. Meanwhile, the AI Anxiety variable is adapted from [3], which measures students' anxiety levels in using AI, their lack of understanding of AI mechanisms, concerns about losing job opportunities, and concerns about the social and ethical impacts of AI. All questionnaire items have been adapted to the context of students' experiences in AI-based learning to ensure relevance and clarity of interpretation.

**Procedures**

This study was conducted through a series of systematic procedures to ensure the validity and reliability of the findings. The procedures used were adapted from a quantitative research framework. Details of the implementation of each stage will be described in the following subsections.

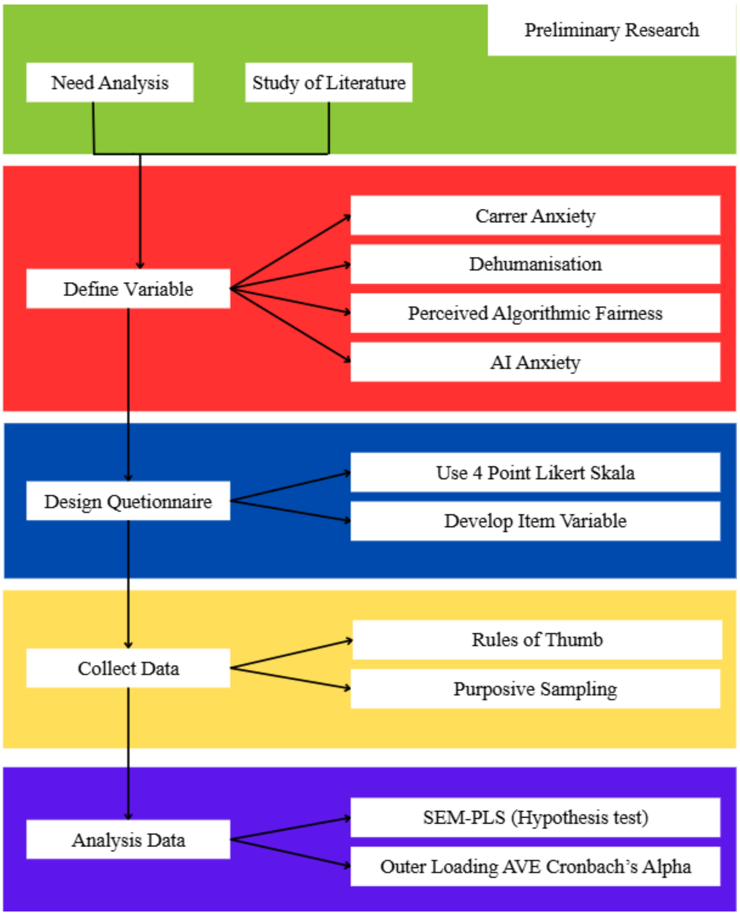


**Figure 1.** Research Procedure

Overall, this study was designed and conducted in a systematic manner, starting from the identification of needs and theoretical review, the determination of research variables, to the development of instruments appropriate for the measurement objectives. The data collection process was carried out in a targeted manner through the selection of relevant respondents, so that the data obtained truly reflected the context of AI technology use in learning. Furthermore, data analysis was conducted using an approach capable of comprehensively testing the relationship between variables through SEM-PLS, accompanied by an evaluation of the measurement model to ensure the quality and reliability of the data used.

**Data Analysis**

Data analysis in this study was conducted through two main stages, namely descriptive analysis and inferential analysis. Descriptive analysis was used to describe the profile of respondents and the trends in responses for each research variable [22]. The results of the descriptive analysis are presented in the form of frequency values, percentages, means, and standard deviations to examine the levels of *Career Anxiety, Dehumanization, Perceived Algorithmic Fairness*, and *AI Anxiety* among students [23]. This stage serves as the basis for ensuring that further analysis is conducted on data whose characteristics and variables have been accurately identified.

Before conducting further analysis, validity and reliability tests were performed using PLS-SEM to ensure that each indicator was capable of measuring the intended variable construct. Construct validity was assessed through Outer Loading, where indicators were considered valid if the loading factor value was ≥ 0.70. Meanwhile, the internal reliability of the instrument was measured using Composite Reliability (CR) and Average Variance Extracted (AVE), with criteria of CR ≥ 0.70 and AVE ≥ 0.50 [17]. With the PLS-SEM approach, measurement models and relationships between variables can be evaluated simultaneously, ensuring that the instruments used are valid, reliable, and stable before proceeding to inferential analysis.

Inferential analysis was performed using Multiple Linear Regression, as this study involved one dependent variable and three independent variables. Before the regression test was conducted, classical assumption testing was performed, including normality, multicollinearity, heteroscedasticity, and linearity tests to ensure the feasibility of the model [24]. The F test is used to determine the simultaneous effect of independent variables, while the t test is used to determine the partial effect. The coefficient of determination ($R^2$) value is used to see how much the independent variables explain the dependent variable. Significance is determined based on a p-value  0.05 as the criterion for accepting the hypothesis.

To illustrate the conceptual framework of this study, a proposed model was developed to analyze the relationship between Career Anxiety, Dehumanization, and Perceived Algorithmic Fairness on AI Anxiety. The model shows how each independent variable potentially contributes to students' anxiety levels in using AI-based technology. The proposed model is presented in Figure 2..

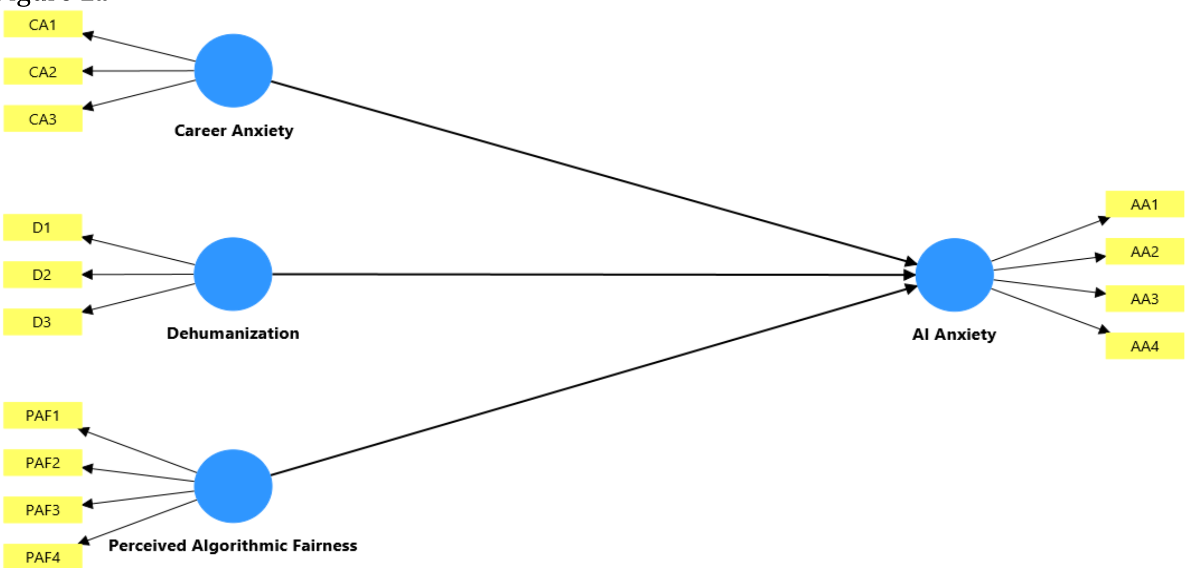


**Figure 2.** Conceptual Model

**Hypothesis**

H1: Career anxiety has a positive effect on AI anxiety
H2: Dehumanization has a positive effect on AI anxiety
H3: Perceived Algorithmic Fairness has a positive effect on AI anxiety

## RESULTS AND DISCUSSION

### Respondent demographics

To provide a clearer picture of the participant profile in this study, demographic data was presented, including gender, age, semester, class year, and field of study. A summary of the respondent distribution is presented in Table 2 below.

**Table 2.** Respondent Demographics

| Category | Subcategory | Counts | % of Total |
|---|---|---|---|
| **Gender** | Male | 28 | 40.0% |
| | Women | 42 | 60.0% |
| **Age** | 17 | 1 | 1.4% |
| | 18 | 5 | 7.1% |
| | 19 | 40 | 57.1% |
| | 20 | 17 | 24.3% |
| | 21 | 3 | 4.3% |
| | 22 | 2 | 2.9% |
| | 23 | 2 | 2.9% |
| **Vacation** | I | 6 | 8.6% |
| | III | 55 | 78.6% |
| | V | 3 | 4.3% |
| | VI | 2 | 2.9% |
| | VII | 2 | 2.9% |
| | IX | 2 | 2.9% |
| **Generation** | 21 | 2 | 2.9% |
| | 22 | 4 | 5.7% |
| | 23 | 4 | 5.7% |
| | 24 | 55 | 78.6% |
| | 25 | 5 | 7.1% |
| **Major** | Non-STEM | 15 | 21.4% |
| | STEM | 55 | 78.4% |
| **Frequency of AI Use in Academic Activities** | 1–2 times a week | 3 | 4.3% |
| | 3–5 times a week | 22 | 31.4% |
| | Rare | 2 | 2.9% |
| | Every Day | 43 | 61.4% |

This study involved 70 students who used AI technology in academic activities, with a composition of 40% male and 60% female. The majority of respondents were 19 years old and in their third semester, indicating that most participants were still in the early stages of their studies. In terms of cohort, 2023 dominated with a percentage of 78.6%, while other cohorts appeared in much smaller numbers. The majority of respondents came from STEM majors with a percentage of 78.4%, while the rest came from non-STEM fields. The frequency of AI use showed high intensity, with 61.4% of students using it every day and 31.4% using it 3–5 times a week.

### Outer Model

The measurement model was evaluated using the PLS-SEM algorithm to examine the quality of the indicators (outer model) and measure the reliability and validity of the constructs.

**Table 3.** Convergent validity

| Construct & Items | Outer Loading | Average Variance Extracted (AVE) |
|---|---|---|
| AI Anxiety (AA) | | |
| AA1 | 0.731 | 0.607 |
| AA2 | 0.809 | |

| | | |
|---|---|---|
| AA3 | 0.761 | |
| AA4 | 0.813 | |
| Career Anxiety (CA) | | |
| CA1 | 0.787 | 0.672 |
| CA2 | 0.787 | |
| CA3 | 0.881 | |
| Dehumanization (D) | | |
| D1 | 0.851 | 0.705 |
| D2 | 0.809 | |
| D3 | 0.857 | |
| Perceived Algorithmic Fairness (PAF) | | |
| PAF1 | 0.811 | 0.516 |
| PAF2 | 0.573 | |
| PAF3 | 0.751 | |
| PAF4 | 0.718 | |

This table presents the results of convergent validity assessment based on the outer loading values and Average Variance Extracted (AVE) of each construct in the model. All indicators in the AI Anxiety, Career Anxiety, and Dehumanization variables have outer loading values greater than 0.70, indicating that these indicators are valid in measuring their constructs. The AVE values for these three constructs are also above 0.50 (0.607-0.705), thus meeting the criteria for convergent validity. Meanwhile, the Perceived Algorithmic Fairness construct has one indicator with a low loading value (0.573), but the resulting AVE value (0.516) is still above the minimum threshold. Overall, this table shows that the measurement model has met the convergent validity standards in PLS-SEM.

**Table 4.** Discriminant Validity (HTMT)

| Construct | AI Anxiety | Career Anxiety | Dehumanization | Perceived Algorithmic Fairness |
|---|---|---|---|---|
| AI Anxiety | | | | |
| Career Anxiety | 0.549 | | | |
| Dehumanization | 0.682 | 0.534 | | |
| Perceived Algorithmic Fairness | 0.414 | 0.561 | 0.430 | |

This table shows the HTMT (Heterotrait-Monotrait Ratio) values to determine the discriminant validity between constructs in the model. All HTMT values are below the threshold of 0.85, indicating that the constructs can be distinguished from one another. The highest correlation is between Dehumanization and AI Anxiety (0.682), which is still within an acceptable range. HTMT values between other constructs also show relatively weak correlations. These results indicate that each variable has a clear construct identity without excessive overlap.

**Table 5.** Construct Reliability

| Construct | Cronbach's Alpha | Composite Reliability (rho_c) |
|---|---|---|
| AI Anxiety | 0.787 | 0.860 |
| Career Anxiety | 0.754 | 0.860 |
| Dehumanization | 0.791 | 0.877 |
| Perceived Algorithmic Fairness | 0.710 | 0.808 |

This table shows Cronbach's Alpha and Composite Reliability (rho c) values used to measure the internal consistency of each construct. All constructs have Cronbach's Alpha values greater than 0.70, indicating that the indicators for each variable have good reliability. The

Composite Reliability values are also greater than 0.80, indicating that the constructs are measured consistently by their items. The Dehumanization construct is assessed to have the highest reliability value (rho c = 0.877), while the Perceived Algorithmic Justice construct has the lowest value but is still above the minimum threshold. Construct reliability - These values indicate that the reliability of all constructs is acceptable in PLS-SEM analysis.

**Inner Model**

This table shows Cronbach's Alpha and Composite Reliability (rho c) values used to measure the internal consistency of each construct. All constructs have Cronbach's Alpha values greater than 0.70, indicating that the indicators for each variable have good reliability. The Composite Reliability values are also greater than 0.80, indicating that the constructs are measured consistently by their items. The Dehumanization construct is rated as having the highest reliability value (rho c = 0.877), while the Perceived Algorithmic Justice construct has the lowest value but is still above the minimum threshold. Construct reliability - These values indicate that the reliability of all constructs is acceptable in PLS-SEM analysis.

**Table 5.** Hypothesis Testing

| Hypothesis | Path Coefficient (β) | T statistics | P values | Description |
|---|---|---|---|---|
| Career Anxiety -> AI Anxiety | 0.234 | 1.691 | 0.045 | Significant |
| Dehumanization -> AI Anxiety | 0.415 | 2.958 | 0.002 | Significant |
| Perceived Algorithmic Fairness -> AI Anxiety | 0.103 | 0.740 | 0.230 | Not Significant |

This table shows how much each independent variable contributes to AI Anxiety. Based on the analysis results, Career Anxiety shows a positive influence with a coefficient value of 0.234 and a p-value of 0.045, so the relationship is considered significant. The Dehumanization variable appears to have the strongest impact on AI Anxiety, as indicated by a coefficient of 0.415 and a p-value of 0.002, which means that the higher the feeling of "not being valued as a human" when using AI, the greater the students' anxiety about the technology. Meanwhile, Perceived Algorithmic Fairness has a weak and insignificant effect ($\beta = 0.103$, $p = 0.230$), so that the perception of AI system fairness is not proven to affect students' anxiety levels.

**Discussion**

The results show that Career Anxiety and Dehumanization have a significant effect on AI Anxiety, while Perceived Algorithmic Fairness does not show a significant effect. These findings confirm that students' anxiety about AI is more influenced by emotional responses and perceptions of personal threats than by cognitive evaluations of system fairness. Dehumanization is the strongest predictor, in line with the view that feelings of loss of human value and reduced autonomy are the main triggers of psychological resistance to technology. International literature also supports this pattern. Haslam states that dehumanization triggers strong negative emotional reactions [25], whereas recent studies show that students tend to experience anxiety when their role in learning is perceived to be replaced by automated systems [8]. In the context of AI-based learning, students who feel that the learning process has become mechanical and overly focused on results tend to experience higher levels of AI Anxiety.

Career Anxiety has also been shown to increase AI Anxiety. This relationship can be explained by concerns about the future of employment as a result of rapid technological automation. In line with the findings [3] as well as [1] students who view AI as a threat to their career opportunities will be more prone to anxiety regarding the use of this technology in learning. Career anxiety is prospective in nature, making students more sensitive to technologies that they perceive as potentially reducing their future professional competitiveness.

Conversely, Perceived Algorithmic Fairness did not have a significant effect on AI Anxiety. This insignificance can be understood because perceptions of algorithmic fairness are rational and normative in nature, and therefore do not directly trigger emotional responses such as anxiety. This is consistent with studies [27] and [28] which shows that fairness has a greater influence on trust and legitimacy of the system than user anxiety. In addition, the dominance of respondents from STEM fields in this study may be one factor explaining these findings. Students with a background in technology tend to view fairness issues as technical problems that can be overcome through system improvements, rather than as a source of emotional threat. Research [11] also shows that students who have a deeper understanding of algorithmic operations tend to assess the fairness of the system more neutrally and do not associate it with emotional burden.

The results of this study are even more relevant when considered in the context of Indonesia's socio-technical environment. Digital transformation in higher education often occurs faster than students' emotional readiness and AI literacy. This situation makes students more prone to dehumanization and career anxiety, especially because they feel they are in a learning system driven by global demands and technological automation without adequate guidance. Meanwhile, the issue of algorithmic fairness has not been a major concern in the Indonesian educational context because the use of AI on campus is more focused on productivity functions than high-risk decision making. Therefore, students' perceptions of algorithmic fairness still have a relatively low impact on their academic lives, so that the impact on AI Anxiety is insignificant.

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**Implications**

Research findings indicate that Career Anxiety and Dehumanization play a significant role in increasing AI Anxiety, so educational institutions need to strengthen student adaptation support through the development of AI literacy, career mentoring programs, and future competency training. These efforts are important because unaddressed career anxiety can reinforce anxiety about technology [29]. Furthermore, since dehumanization is the strongest predictor, it is necessary to implement a human-centered approach that emphasizes that AI serves as a supporting tool, not a substitute for human values. This approach is in line with the findings [30] which emphasizes that dehumanization can increase technological anxiety, so that transparency of AI working mechanisms, ethical use, and clear communication about the role of technology are important aspects for creating a safer AI-based learning experience that does not cause anxiety for students.

**Research Contribution**

This study makes an important contribution to the literature on technology anxiety by showing that emotional aspects such as dehumanization and career anxiety are more dominant than cognitive perceptions such as fairness. This study also enriches empirical evidence in the Indonesian context, which has previously been understudied in AI Anxiety research. From a methodological perspective, this study demonstrates how PLS-SEM can be used to test psychological relationships in the context of AI adoption.

**Limitations**

This study still has limitations, including the composition of respondents, which is dominated by STEM students, so the results do not fully reflect cross-disciplinary perceptions. In addition, the cross-sectional design of the study does not allow researchers to see changes in perceptions as AI technology develops. The variables analyzed are also limited to internal psychological factors, so they do not cover external factors such as experience using AI or the influence of the media.

**Suggestions**

This study still has limitations, including the composition of respondents, which is dominated by STEM students, so the results do not fully reflect cross-disciplinary perceptions. In addition, the cross-sectional design of the study does not allow researchers to see changes in perceptions as AI technology develops. The variables analyzed are also limited to internal psychological factors, so they do not cover external factors such as experience using AI or the influence of the media.

## CONCLUSIONS

This study shows that AI Anxiety among students is mainly influenced by two main factors, namely Career Anxiety and Dehumanization, while Perceived Algorithmic Fairness does not have a significant effect. These findings contribute theoretically by reaffirming the position of Socio-Technical Systems Theory in explaining how socio-emotional aspects can influence psychological responses to technology. Methodologically, this study reinforces the use of PLS-SEM in analyzing complex psychological relationships in the context of AI-based education, especially with constructs involving emotional dimensions and user perceptions. From a practical standpoint, this study provides empirical evidence that the integration of AI in higher education needs to focus on a human-centered approach and more structured career adaptation strategies to help students cope with technological change in a healthy manner.

This study shows that AI Anxiety among students is mainly influenced by two main factors, namely Career Anxiety and Dehumanization, while Perceived Algorithmic Fairness does not have a significant effect. These findings contribute theoretically by reaffirming the position of Socio-Technical Systems Theory in explaining how socio-emotional aspects can influence psychological responses to technology. Methodologically, this study reinforces the use of PLS-SEM in analyzing complex psychological relationships in the context of AI-based education, especially with constructs involving emotional dimensions and user perceptions. From a practical perspective, this study provides empirical evidence that the integration of AI in higher education needs to focus on a human-centered approach and more structured career adaptation strategies to help students cope with technological change in a healthy manner.

Thus, this study has several limitations that directly implicate the validity and generalization of the findings. The composition of respondents, which was dominated by STEM students, limits the ability to generalize to a population of students across disciplines. The cross-sectional nature of the study also poses a threat to internal validity because it does not allow researchers to observe changes in perceptions or anxiety over time. Furthermore, the use of self-report questionnaires has the potential to introduce perceptual bias that can affect the accuracy of psychological construct measurements. These limitations indicate that the results of this study should be interpreted with caution, especially when applied to different educational contexts or populations.

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## REFERENCES

[1] J. Kim *et al.*, "AI Anxiety: A Comprehensive Analysis of Psychological Factors and Interventions," *SSRN Electronic Journal*, 2023, doi: 10.2139/ssrn.4573394.

[2] D. G. Johnson and M. Verdicchio, "AI Anxiety," *J Assoc Inf Sci Technol*, 2017, [Online]. Available: https://doi.org/10.1002/asi.23867

[3] Y. Y. Wang and Y. S. Wang, "Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior," *Interactive Learning Environments*, vol. 30, no. 4, pp. 619–634, 2022, doi: 10.1080/10494820.2019.1674887.

[4] I. A. Batubara, W. Wariyati, and Y. D. Prawiyata, "Exploring University Students' Perceptions of AI: Insights from Indonesia," *Edu Cendikia: Jurnal Ilmiah Kependidikan*, vol. 4, no. 03, pp. 1687–1701, 2025, doi: 10.47709/educendikia.v4i03.5465.

[5] S. P. T. Utami, Andayani, R. Winarni, and Sumarwati, "Utilization of artificial intelligence technology in an academic writing class: How do Indonesian students perceive?," *Contemp Educ Technol*, vol. 15, no. 4, 2023, doi: 10.30935/cedtech/13419.

[6] R. Saputra, T. Tiolince, Iswantoro, and S. K. Sigh, "Artificial Intelligence and Intellectual Property Protection in Indonesia and Japan," *Journal of Human Rights, Culture and Legal System*, vol. 3, no. 2, pp. 210–235, 2023, doi: 10.53955/jhcls.v3i2.69.

[7] E. Trist, "The Evolution of socio-technical systems: a conceptual framework and action research program," 1980. doi: 0-7743-6286-3.

[8] C. Longoni, A. Bonezzi, and C. K. Morewedge, "Resistance to Medical Artificial Intelligence," *Journal of Consumer Research*, vol. 46, no. 4, pp. 629–650, 2019, doi: 10.1093/jcr/ucz013.

[9] R. Farrow, "The possibilities and limits of XAI in education: a socio-technical perspective," *Learn Media Technol*, vol. 48, no. 2, pp. 266–279, 2023, doi: 10.1080/17439884.2023.2185630.

[10] B. T. Alshahrani, S. F. Pileggi, and F. Karimi, "A Social Perspective on AI in the Higher Education System: A Semisystematic Literature Review," *Electronics (Switzerland)*, vol. 13, no. 8, pp. 1–27, 2024, doi: 10.3390/electronics13081572.

[11] D. Martín-Moncunill and D. Alonso Martínez, "Students' Trust in AI and Their Verification Strategies: A Case Study at Camilo José Cela University," *Educ Sci (Basel)*, vol. 15, no. 10, p. 1307, 2025, doi: 10.3390/educsci15101307.

[12] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education – where are the educators?," *International Journal of Educational Technology in Higher Education*, vol. 16, no. 1, 2019, doi: 10.1186/s41239-019-0171-0.

[13] A. Ghanad, "An Overview of Quantitative Research Methods," *International Journal of Multidisciplinary Research and Analysis*, vol. 06, no. 08, pp. 3794–3803, 2023, doi: 10.47191/ijmra/v6-i8-52.

[14] H. Bentouhami, L. Casas, and J. Weyler, "Reporting of 'theoretical design' in explanatory research: A critical appraisal of research on early life exposure to antibiotics and the occurrence of asthma," *Clin Epidemiol*, vol. 13, pp. 755–767, 2021, doi: 10.2147/CLEP.S318287.

[15] C. L. Lai, "Exploring University Students' Preferences for AI-Assisted Learning Environment: A Drawing Analysis with Activity Theory Framework," *Educational Technology and Society*, vol. 24, no. 4, pp. 1–15, 2021, [Online]. Available: https://www.jstor.org/stable/48629241

[16] A. Bozkurt and R. C. Sharma, "Challenging the Status Quo and Exploring the New Boundaries in the Age of Algorithms: Reimagining the Role of Generative AI in Distance Education and Online Learning," *Asian Journal of Distance Education*, vol. 18, no. 1, p. 2023, 2023, [Online]. Available: http://www.asianjde.com/

[17] J. F. Hair, G. T. Hult, C. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) - Joseph F. Hair, Jr., G. Tomas M. Hult, Christian Ringle, Marko Sarstedt*. 2017. [Online]. Available: http://lccn.loc.gov/2016005380

[18] M. Koo and S. Yang, "Likert-Type Scale," pp. 1–11, 2025, doi: 10.3390/encyclopedia5010018.

[19] M. S. Mahmud, M. M. Rahman, M. Masud-Ul-Hasan, and M. A. Islam, "Does 'COVID-19 phobia' stimulate career anxiety?: Experience from a developing country," *Heliyon*, vol. 7, no. 3, p. e06346, 2021, doi: 10.1016/j.heliyon.2021.e06346.
[20] B. Pizzirani, G. C. Karantzas, and E. R. Mullins, "The Development and Validation of a Dehumanization Measure Within Romantic Relationships," *Front Psychol*, vol. 10, no. December, pp. 1–16, 2019, doi: 10.3389/fpsyg.2019.02754.
[21] A. A. S. Rasel, A. M. Amlan, T. S. Mim, and T. Hasan, "A Methodological Framework and Questionnaire for Investigating Perceived Algorithmic Fairness," no. Ml, pp. 1–34, 2025, [Online]. Available: http://arxiv.org/abs/2508.05281
[22] S. Loeb, S. Dynarski, D. McFarland, P. Morris, S. Reardon, and S. Reber, "Descriptive analysis in education: A guide for researchers," *U.S. Department of Education, Institute of Education Sciences. National Center for Education Evaluation and Regional Assistance*, no. March, pp. 1–40, 2017, [Online]. Available: https://eric.ed.gov/?id=ED573325
[23] H. Stone, J. L. Sidel, and J. Bloomquist, "Quantitative Descriptive Analysis," *Descriptive Sensory Analysis in Practice*, pp. 93–69, 2008, doi: 10.1002/9780470385036.ch1f.
[24] M. D. Irrawati and M. Mukaramah, "Implementasi Metode Regresi Linear Berganda untuk Mengatasi Pelanggaran Asumsi Klasik ( Implementation of Multiple Linear Regression Methods to Overcome Violations of Classical Assumptions )," vol. 3, no. 2, pp. 83–94, 2024, doi: 10.35912/sakman.v3i2.2743.
[25] N. Haslam, "Dehumanization : An Integrative Review," vol. 10, no. 3, pp. 252–264, 2006, doi: 10.1207/s15327957pspr1003_4.
[26] R. F. Kizilcec and H. Lee, "Algorithmic fairness in education," *The Ethics of Artificial Intelligence in Education: Practices, Challenges, and Debates*, pp. 174–202, 2022, doi: 10.4324/9780429329067-10.
[27] J. Ochmann, L. Michels, V. Tiefenbeck, C. Maier, and S. Laumer, "Perceived algorithmic fairness: An empirical study of transparency and anthropomorphism in algorithmic recruiting," *Information Systems Journal*, vol. 34, no. 2, pp. 384–414, 2024, doi: 10.1111/isj.12482.
[28] R. Li, J. Ouyang, J. Lin, and S. Ouyang, "Mediating effect of AI attitudes and AI literacy on the relationship between career self-efficacy and job-seeking anxiety," *BMC Psychol*, vol. 13, no. 1, 2025, doi: 10.1186/s40359-025-02757-2.
[29] C. Zhang and Y. Lu, "Study on artificial intelligence: The state of the art and future prospects," *J Ind Inf Integr*, vol. 23, no. March, p. 100224, 2021, doi: 10.1016/j.jii.2021.100224.