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The Role of Artificial Intelligence Anxiety and Attitudes Toward Artificial Intelligence in University Students' Job Finding Anxiety

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The spread of artificial intelligence in the labor market is reshaping students' employment expectations and creating concerns about the job search process. This study examines how students' artificial intelligence related anxiety and attitudes influence their post graduation job finding anxiety. Although individual attitudes and concerns related to artificial intelligence have been increasingly explored in recent years, limited research has directly addressed the relationship between these variables and labor market-related concerns. There remains a need for multivariate studies with large samples that comprehensively investigate the interplay between technological transformation and employment uncertainty. This quantitative research employed a correlational survey design and included 1,057 students from various faculties and departments across 35 universities in Türkiye. Data were collected through online surveys using convenience and snowball sampling methods. The analysis involved statistical techniques such as correlation, independent samples t-test, ANOVA, and Cohen's d. The findings showed that higher anxiety and negative attitudes toward artificial intelligence are positively associated with job finding anxiety. In addition, female students, social science majors, and second year students reported higher anxiety levels. The results were interpreted within the frameworks of the Technology Acceptance Model and Social Cognitive Career Theory, suggesting that students' perceptions of technological transformation influence their career planning and sectoral expectations. In this context, the study underlines the need for a review of higher education policies to better support students' career paths in the age of artificial intelligence.

Introduction

Individuals graduating from higher education institutions increasingly face uncertainty and intense competition when entering the labor market. The growing number of graduates each year, coupled with limited employment opportunities and ongoing economic fluctuations, has made Job Finding Anxiety widespread and deepening concern among university students and recent graduates. According to the Ministry of Education of the People's Republic of China (MoE, 2024), more than 11.8 million students are expected to

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graduate in China in 2024, underlining the magnitude of global competitive pressure in the labor market.

In this context, the rapid proliferation of artificial intelligence (AI) and automation technologies in the business world has emerged as a significant factor influencing graduates' concerns about securing employment. The potential of AI to replace human labor across various industries has triggered concrete anxieties, encapsulated in questions such as "Will a robot take my job?" (Chen et al., 2025). This issue reflects a complex phenomenon that encompasses not only technical aspects but also psychological and social dimensions. University students form varying attitudes toward the impact of AI on their future professions some perceive it as an opportunity, while others regard it as a serious threat (Tsenov & Bakracheva, 2025).

International organizations are actively monitoring the implications of this technological transformation. According to UNESCO's *Generation AI Report* (2023), while AI creates considerable opportunities in education, it simultaneously generates uncertainty among students on ethical, psychological, and professional levels. Similarly, the OECD's *Employment Outlook Report* (2023) highlights that AI and automation are reshaping the global labor market, with approximately 27% of existing jobs in OECD member countries at risk of automation. This ongoing transformation not only emphasizes the need for new skill sets but also intensifies individuals' concerns about job security.

The existing literature increasingly highlights that individuals' concerns about AI and their attitudes toward this technology are associated with their career planning and psychological well-being (Cengiz & Peker, 2025; Obenza et al., 2024). However, there remains a limited body of research investigating the direct impact of these concerns and attitudes on post-graduation employment anxiety (Cengiz & Peker, 2025; Morales-García et al., 2025; Uçar et al., 2025). How university students' AI-related concerns and evaluations of this technology influence their employment-related emotional states has not yet been sufficiently explored.

At this point, examining how students' anxiety related to the post-graduation job search is shaped by their individual concerns and attitudes toward AI contributes to the academic literature and addresses a critical gap in the development of higher education policies. This study aims to explore the extent to which university students' concerns and attitudes regarding AI are associated with their Job Finding Anxiety after graduation. In an era of rapid technological transformation and the widespread integration of AI into the workforce, understanding students' psychological responses to these changes is essential for preparing them more effectively for the demands of the labor market.

Purpose and Significance of the Study

The main purpose of this study is to examine the relationship between university students' post-graduation Job Finding Anxiety, AI Anxiety, and AI Attitudes. Thus, it will be revealed how individual psychological variables affect Job Finding Anxiety in an environment of uncertainty brought about by technological transformation. Uçar et al. (2025) made a significant contribution to the field by revealing the relationship between AI Anxiety and Job Finding Anxiety among university students. However, the fact that the participants in the study were limited to a single university may limit the generalizability of the findings. In this context, the current study, conducted with a broader sample of students from different universities and departments, aims to address the impact of AI Anxiety and AI Attitudes levels on Job Finding Anxiety, thereby providing a more comprehensive perspective on this important topic. At this point, the hypotheses of the study are as follows:

- H1: Job Finding Anxiety is related to AI Anxiety and AI Attitudes.
- H2a: Job Finding Anxiety is significantly higher in female than in male.
  H2b: AI Anxiety is significantly higher in female than in male.
- H3: There is a difference between academic year levels in terms of Job Finding Anxiety.
- H4: Job Finding Anxiety is significantly lower in students studying in natural and applied fields.

Literature Review

H1: Job Finding Anxiety is related to AI Anxiety and AI Attitudes

In recent years, rapid advances in AI have significantly shaped young people's career expectations and perceptions of job security. University students' Job Finding Anxiety is influenced not only by perceived competence but also by AI Anxiety and AI Attitudes. Accordingly, the study is based on Social Cognitive Career Theory (SCCT) (Lent et al., 1994) and the Technology Acceptance Model (TAM) (Davis, 1989).

SCCT explains career development through self efficacy, outcome expectations, and goal setting. Research shows that higher self efficacy lowers anxiety and increases motivation. For example, Li et al. (2025) found that Chinese students with high career self efficacy showed stronger Positive AI Attitudes and reduced Job Finding Anxiety. TAM explains technology acceptance through perceived usefulness and ease of use. Accordingly, Positive AI Attitudes can reduce AI Anxiety, while Negative AI Attitudes may hinder adaptation. Migdadi et al. (2024) supported this by showing that AI Anxiety was positively related to the intention to use AI among nursing students, suggesting that anxiety may sometimes encourage preparation rather than avoidance.

However, studies also show that high AI Anxiety and Negative AI Attitudes can increase Job Finding Anxiety. Uçar et al. (2025) found a moderate positive correlation in Türkiye, noting that students with low confidence reported both high AI Anxiety and high Job Finding Anxiety. Similarly, Morales-García et al. (2025) found that strong concerns about AI increased vulnerability to labor market uncertainty in Peru. Other studies also show that Negative AI Attitudes weaken professional confidence and performance. For example, Özçevik-Subaşı et al. (2024) reported that AI-related stress reduced nurses' performance, while Schiavo et al. (2024) noted that high AI Anxiety hindered adaptation to innovation. Westover (2024) also noted that Generation Z faces AI related stress due to limited experience and uncertainty about technological change, which increases Job Finding Anxiety.

H2a: Job Finding Anxiety is significantly higher in females than in males

The rapid spread of digitalization and AI has heightened uncertainty about post-graduation employment, increasing Job Finding Anxiety. Studies show that this anxiety is especially high among females. This hypothesis is based on SCCT (Lent et al., 1994) and TAM (Davis, 1989). SCCT emphasizes that career related thoughts and behaviors are shaped by self efficacy, outcome expectations, and goal setting processes. Gender roles often make it harder for women to see themselves as competent in technological fields, increasing uncertainty and stress (Hackett & Betz, 1981; Fouad & Santana, 2017). This can lead to negative outcome expectations and higher Job Finding Anxiety (Byars-Winston & Rogers, 2019). Additionally, rising demands for technological competence in the labor market further intensify women's concerns.

Empirical findings support this view. Uçar et al. (2025) found a positive relationship between AI Anxiety and Job Finding Anxiety in Türkiye, reporting that low trust in technology increased anxiety levels. Similarly, Özçevik-Subaşı et al. (2024) showed that AI-related stress reduced nurses' professional confidence and performance. Similarly, Schiavo et al. (2024) found that high AI Anxiety lowered adaptation and motivation, and Westover (2024) noted that female members of Generation Z reported higher anxiety than males. Together, these studies show that female develop stronger feelings of uncertainty and inadequacy during technological change. Within SCCT and TAM, these perceptions increase Job Finding Anxiety. Thus, examining gender's role in shaping this anxiety is important both theoretically and practically.

H2b: AI Anxiety is significantly higher in females than in males.

With the growing use of AI in education, individuals' attitudes and psychological responses have become an important research focus. AI Anxiety is a multidimensional emotional state arising from factors such as learning difficulties, job insecurity, technical incompatibility, and socio-technical unawareness. Recent studies show that this anxiety differs across individual variables, especially gender.

İlhan (2025) found that female pre-service English teachers reported significantly higher AI Anxiety than males in the dimensions of job loss, AI learning, and AI structuring. The study also showed that female students had higher intrinsic motivation alongside higher overall AI Anxiety. These findings are also consistent with broader psychological anxiety research. Hosseini and Khazali (2013) reported that female students scored higher than male students on the dimensions of physiological anxiety and worry. In addition, female students were found to experience higher levels of anxiety in academic contexts, including test anxiety, mathematics anxiety, and general exam performance anxiety (Núñez-Peña et al., 2016). These results support the hypothesis that female students are more sensitive to factors such as technological uncertainty and employment insecurity in the context of AI Anxiety. This sensitivity can further increase general anxiety levels.

H3: There is a difference between academic year levels in terms of Job Finding Anxiety

University students' Job Finding Anxiety is influenced not only by individual differences but also by developmental and cognitive processes. Career expectations, stress levels, and plans may vary significantly depending on students' grade level. This hypothesis can be grounded in Super's Lifespan Career Development Theory (Super, 1980) and Lazarus and Folkman's (1984) Cognitive Appraisal Theory.

According to Super, career development is a lifelong, multi-stage process. University students occupy different stages of this process; senior students may experience more intense Job Finding Anxiety due to their proximity to the labor market (Super, 1980). This proximity can heighten stress levels by threatening the balance between career identity and external reality. For students in earlier grades, the job search process tends to be perceived more abstractly.

Lazarus and Folkman's (1984) Cognitive Appraisal Theory emphasizes that stress is determined more by individuals' evaluations of conditions than by the objective conditions themselves. As graduation approaches, the job search process is increasingly appraised as a "threat," and individuals with low self-efficacy experience this threat perception more intensely.

Empirical studies lend support to this framework. Li et al. (2025) demonstrated that students with high career self-efficacy developed more Positive AI Attitudes and reported lower levels of Job Finding Anxiety. Uçar et al. (2025) identified a positive relationship between AI Anxiety and Job Finding Anxiety, showing that students with low trust in technology experienced heightened anxiety. Similarly, Morales-García et al. (2025) and Westover (2024) observed that technological transformation generates intense stress regarding employment among young individuals. This stress appears particularly pronounced among final-year students, whose growing concerns about job security and technological adaptation lead them to appraise the job search process as an "insurmountable" threat.

H4: Job Finding Anxiety is significantly lower in students studying in natural and applied fields.

University students' post graduation Job Finding Anxiety levels may vary not only because of individual differences but also across academic disciplines. Students in natural and applied fields are more directly engaged with technology, which facilitates their adaptation to digital transformation and may, in turn, lower their Job Finding Anxiety levels. This hypothesis can be explained within the framework of Expectancy Value Theory (Eccles & Wigfield, 2002).

According to Expectancy Value Theory, individuals' efforts in each field are shaped by both their expectations of success and the value they attribute to the task. Students in natural and applied fields may hold higher expectations of success and assign greater value to such tasks because they are exposed to AI and digital systems at an earlier stage of their education. Consequently, the uncertainties brought about by technological transformation are perceived as less threatening by these students.

Empirical findings further support this framework. Migdadi et al. (2024) identified a positive relationship between AI Anxiety and the intention to use technology, demonstrating that anxiety can, in some cases, increase interest and readiness. This finding may be particularly relevant for students in natural and applied fields. By contrast, Schiavo et al. (2024) reported that students with high levels of AI Anxiety exhibited weaker tendencies toward innovation adaptation and motivation. This suggests that anxiety among students in non-natural and applied fields may intensify threat perceptions, thereby raising Job Finding Anxiety. In conclusion, expectancy value components play a decisive role in shaping students' career-related anxiety. Students in natural and applied fields tend to experience lower levels of Job Finding Anxiety because of their higher expectations of success and stronger perceptions of technological value.

Method

Research design

The research design of this study is a correlational survey design within the scope of quantitative research approaches. A correlational survey design is a type of design aimed at describing the relationships between variables and determining the direction and level of these relationships (Karasar, 2022). In this context, the study aims to examine the relationship between university students' post-graduation Job Finding Anxiety and AI Anxiety and AI Attitudes. In the study, the current situation was evaluated in its natural environment without any experimental procedures or interventions. The participants' views were collected through three different scales, and correlational analyses were conducted between the variables based on the data obtained. In this respect, the study is a descriptive correlational study that aims to reveal the causal relationships between the variables.

Research group

The data for the study were collected online using Google Forms between February 15 and April 15, 2025. The study aimed to reach the maximum number of participants; data were collected using appropriate sampling and snowball sampling methods. First, 232 students studying at the university where the researchers worked were identified using the appropriate sampling method. "Convenience sampling is a method in which units that are close by and easy to reach are selected as samples" (Yıldırım & Şimşek, 2021). In line with the research objectives, it was thought that students' Job Finding Anxiety, AI Anxiety and AI Attitudes scores might vary depending on the universities and departments they were studying at. For this reason, snowball sampling was used as the second sampling method. According to the snowball sampling technique, first, contact is made with one of the units belonging to the population. Then, with the help of the unit contacted, the second unit is reached, and with the help of the second unit, the third unit is reached. The process continues in this way (Yazıcıoğlu & Erdoğan, 2004). Each unit reached through another unit forms a link in the chain. This technique can also be referred to as the chaining technique. With the help of the people reached, more people are included in the list, and the list grows like a snowball (Yıldırım & Şimşek, 2021). In this context, the researchers first established contact with their acquaintances from different universities. Subsequently, second contact was made with individuals recommended and referred to by these acquaintances from different universities, and the universities from which data would be collected were determined. Within this scope, a total of 842 students from 34 universities were included in the study using the snowball sampling method. Thus, the research group for this study consists of 1,074 students from 80 different departments, grouped into natural and applied and social sciences, at 35 universities, who voluntarily agreed to participate in the study. The dataset was examined for missing values, and no missing data were identified (Field, 2024). Given the absence of missing values, outlier analysis was performed in the next step. For this purpose, all variable scores were converted into standardized z-scores, and values were assessed based on the ±3 threshold (Tabachnick & Fidell, 2014). A total of 17 observations that fell outside this range were identified as outliers and subsequently excluded from the dataset. The final analysis was conducted on the remaining 1,057 observations. The gender distribution of the students (F: 616, M: 441) is shown in Figure 1.

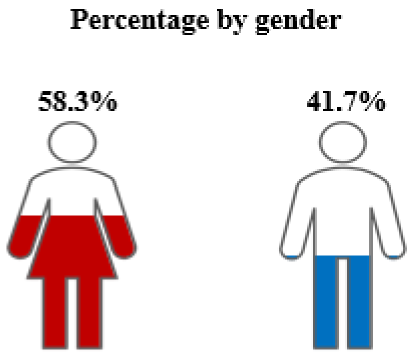


Figure 1. Distribution of students by gender.

Figure 2 shows the distribution of students by field. Consequently, social science fields enroll 609 students (57.6%), while natural and applied fields enroll 448 students (42.4%).

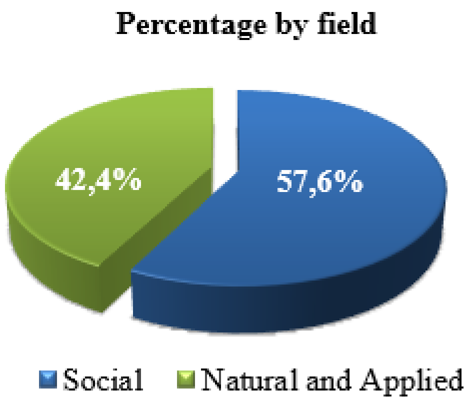
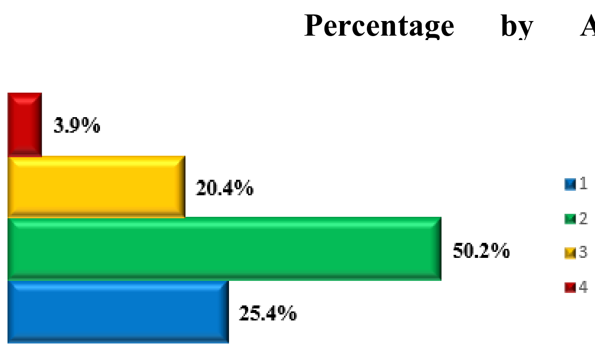


Figure 2. Distribution of students according to their fields of study.

Figure 3 presents the distribution of students by academic year. 50.2% of the participants are second-year students, indicating that they represent the largest group in the sample.



Academic Year	Count
1	269
2	531
3	216
4	41
	1057

Figure 3. Distribution of students according to academic year.

Data collection tools

In this study, the Job Finding Anxiety, AI Anxiety, and AI Attitudes scales were used as data collection instruments. The selection of these measurement tools was guided by the study's objective to examine the relationships between Job Finding Anxiety, AI Anxiety, and AI Attitudes among university students in the context of post graduation employment.

Job Finding Anxiety scale

The Job Finding Anxiety scale, developed by Boğazlıyan and Avşaroğlu (2024), consists of 19 items and four subscales: Incompetence Anxiety, Proximity Anxiety, Discrimination Anxiety, and Country Conditions Anxiety. The validity and reliability of the scale were tested using exploratory factor analysis (Cronbach's α=.933) with 200 participants and confirmatory factor analysis with 448 participants The scale showed acceptable levels of fit (χ^2/df=3.76; RMSEA=.079; SRMR=.056).

AI Anxiety scale

The AI Anxiety Scale developed by Wang and Wang (2019) and adapted into Turkish by Terzi (2020), consists of 21 items and is rated on a 7-point Likert scale ranging from 1 ("Never") to 7 ("Completely"). The scale has been validated using data from 301 participants and has demonstrated high internal consistency (Cronbach's α=.964). The scale has a four-factor structure and consists of the dimensions of Learning, Job Displacement, Sociotechnical Blindness, and Configuration. Confirmatory factor analysis results indicate that the scale's model fit is acceptable [χ^2/df=2.57; TLI=.93; CFI=.94; SRMR=.069; RMSEA=.084].

AI_Attitudes scale

Çakan and Akın (2024) adapted the Internet Attitude Scale developed by Durndell and Haag (2002) into Turkish. The adapted Artificial Intelligence Attitude Scale consists of 12 items and is measured on a five-point Likert scale ranging from 1 ("Strongly disagree") to 5 ("Strongly agree"). The scale contains two subscales: Negative AI Attitudes and Positive AI Attitudes. Confirmatory factor analysis results showed acceptable levels of fit (χ^2/df=10.66; RMSEA=.075; SRMR=.067). When examining the reliability coefficients of the scale, Cronbach's α value for the entire scale was calculated as .826.

A first-order CFA was conducted on our sample for the AI Attitudes scale, yielding the following fit indices: χ2/df=3.88, TLI=.974, CFI=.979, RMSEA=.052, SRMR=.063. According to Hu and Bentler (1999), χ2/df is acceptable (between 3 and 5), TLI is excellent (>.95), CFI is excellent (>.95), RMSEA is excellent (<.06), and SRMR is excellent (<.08). Therefore, model fit has been achieved for the AI Attitudes scale.

When the reliability analysis was conducted in this study, Cronbach's alpha of the Job Finding Anxiety Scale was calculated as .929. However, Cronbach's alpha of the AI Anxiety Scale was .962, while that of the AI_Attitudes Scale was .826. In social science research, coefficients between $.80 \leq \alpha < .90$ indicate "very good" internal consistency, while coefficients of .90 and above indicate "excellent internal consistency" (Kline, 2005; Tavşancıl, 2014). Three measurement tools are highly reliable.

Data analysis

The data obtained in the study were analyzed using IBM SPSS Statistics (Version 25; IBM Corp., 2017), RStudio (Version 4.5.0 [2024-04-11]; R Core Team, 2024), Microsoft Excel for Microsoft 365 (Microsoft Corporation, 2021), and Jamovi (Version 2.6.26; The jamovi project, 2024). These softwares were utilized to conduct descriptive and inferential statistical analyses throughout the study.

Skewness and kurtosis coefficients were examined to assess the univariate normality of the dataset. The results indicated that the skewness and kurtosis values for both total and mean scores of the scales fell within the acceptable range of ±1. This finding suggests that the assumption of univariate normality was met.

The relationships between the total and mean scores of the scales and their subdimensions were examined using Pearson's correlation coefficient. Before the group comparisons, homogeneity of variances for gender, field of study, and grade level was tested and found to be satisfied. Accordingly, the use of parametric tests was deemed appropriate for analyzing differences between groups.

To examine differences in the variables based on participants' demographic characteristics, independent samples t-tests were conducted for gender and field of study. For the academic year level, one-way analysis of variance (ANOVA) was used.

Findings

Descriptive statistics for the demographic variables, as well as the mean scores of the scales and their subdimensions, are presented in Table 1. The remaining findings derived from the data analyses are presented below in accordance with the research hypotheses.

Table 1. Descriptive statistics of mean scores by demographic variables.

			Gender		Field of Study		Academic Year			
Scale	Factors		Female	Male	Social	Natural and Applied	1	2	3	4
AI Anxiety	Learning	M	2.959	2.584	2.858	2.729	2.580	2.901	2.841	2.789
		SD	1.354	1.418	1.392	1.393	1.352	1.438	1.301	1.412
	Job Displacement	M	4.068	3.189	3.830	3.527	3.615	3.725	3.697	3.955
		SD	1.591	1.727	1.699	1.699	1.810	1.656	1.642	1.941
	Sociotechnical Blindness	M	4.092	3.302	3.900	3.576	3.656	3.800	3.748	4.042
		SD	1.608	1.769	1.699	1.736	1.745	1.695	1.709	1.963
	Configuration	M	3.995	2.994	3.732	3.369	3.371	3.599	3.713	3.943
		SD	1.785	1.783	1.823	1.870	1.886	1.815	1.809	2.194
	Total	M	3.640	2.952	3.459	3.210	3.194	3.408	3.383	3.526
		SD	1.282	1.436	1.369	1.407	1.378	1.387	1.370	1.560
AI Attitudes	Negative AI Attitudes	M	3.437	2.938	3.295	3.143	3.180	3.184	3.381	3.365
		SD	.918	1.100	.998	1.062	1.039	1.050	.939	1.042
	Positive AI Attitudes	M	3.494	3.510	3.468	3.546	3.527	3.519	3.438	3.424
		SD	.882	1.097	.949	1.015	1.022	.988	.900	.943

	Total	M	3.462	3.176	3.367	3.311	3.324	3.323	3.405	3.390
		SD	.777	.925	.833	.880	.867	.865	.801	.886
Job Finding Anxiety	Incompetence Anxiety	M	3.137	2.694	3.030	2.847	2.841	3.039	2.874	2.970
		SD	.950	1.073	1.015	1.034	1.081	1.021	.979	.882
	Proximity Anxiety	M	3.250	2.653	3.120	2.873	2.887	3.128	2.874	3.126
		SD	1.047	1.159	1.108	1.146	1.171	1.098	1.149	1.005
	Discrimination Anxiety	M	2.403	2.074	2.371	2.123	2.150	2.324	2.278	2.201
		SD	.925	.913	.953	.889	.885	.972	.894	.903
	Country Conditions Anxiety	M	3.474	2.983	3.367	3.138	3.180	3.350	3.150	3.424
		SD	.970	1.106	1.032	1.077	1.132	1.006	1.080	.975
	Total	M	3.100	2.638	3.004	2.778	2.797	2.994	2.821	2.969
		SD	.809	.936	.886	.889	.935	.874	.889	.770

Table 1 shows that female students exhibit higher levels of AI Anxiety (M=3.64), Negative AI Attitudes (M=3.44), and Job Finding Anxiety (M=3.10) compared to male students. Regarding attitudes toward AI, females reported more Negative AI Attitudes(M=3.44) than males (M=2.94). In contrast, the mean scores for Positive AI Attitudes were relatively similar across genders.

Significant differences were observed in AI Anxiety, AI Attitudes, and Job Finding Anxiety based on students' field of study. Students majoring in social sciences reported higher levels of AI Anxiety (M=3.46) compared to those in natural and applied fields (M=3.21). Similarly, their Negative AI Attitudes was slightly higher (M=3.37). In terms of Job Finding Anxiety, social science students also exhibited higher mean scores (M=3.00) than their counterparts in natural and applied fields (M=2.78).

When examined by grade level, significant differences were observed in students' levels of AI Anxiety and Job Finding Anxiety. Notably, second year students reported the highest levels of anxiety among all grade levels, with mean scores of M=3.41 for AI Anxiety and M=2.99 for Job Finding Anxiety. In contrast, the highest mean score for AI Attitudes was observed among third year students (M=3.41).

H1: Job Finding Anxiety is related to AI Anxiety and AI Attitudes.

The relationships between the total and mean scores of the scales and their subdimensions were examined using Pearson's correlation coefficient, and the results are presented in Table 2. As shown in the table, all correlations are statistically significant ($p \leq .05$).

Table 2. Pearson correlation coefficients between total and mean scores of the Job Finding Anxiety, AI Anxiety and AI Attitudes scales and their subdimensions.

	JFA INA	JFA PRX	JFA DSC	JFA CNT	JFA	AIA NEG	AIA POS	AIA	AIAS L	AIAS J	AIAS S	AIAS C	AIAS
JFA INA	1												
JFA PRX	.773*	1											
JFA DSC	.525*	.492*	1										
JFA CNT	.710*	.787*	.431*	1									
JFA	.896*	.919*	.676*	.882*	1								
AIA NEG	.343*	.387*	.273*	.393*	.415*	1							
AIA POS	.257*	.266*	.122*	.304*	.288*	.416*	1						
AIA	.364*	.399*	.250*	.421*	.429*	.901*	.769*	1					
AIAS L	.437*	.418*	.498*	.337*	.485*	.413*	.119*	.347*	1				
AIAS J	.436*	.436*	.352*	.441*	.491*	.608*	.225*	.535*	.557*	1			
AIAS S	.433*	.448*	.335*	.456*	.496*	602*	.264*	.549*	.546*	.845*	1		
AIAS C	.390*	.404*	.354*	.399*	.455*	.603*	.145*	.493*	.539*	.773*	.798*	1	
AIAS	.496*	.495*	.460*	.466*	.561*	.628*	.214*	.543*	.808*	.909*	.892*	.855*	1

*:p ≤ .05

Note: Due to the high density of data in this table, variables have been abbreviated.

Firstly, strong positive correlations were observed between the Job Finding Anxiety and its subdimensions: Incompetence Anxiety (r=.896), Proximity Anxiety (r=.919), Discrimination Anxiety (r=.676) and Country Conditions Anxiety (r=.882). Similarly, AI Anxiety showed strong positive correlations with its subdimensions: Configuration (r=.855), Sociotechnical Blindness (r=.892), Job Displacement (r=.909) and Learning (r=.808).

A moderate, positive, and statistically significant relationship was found between Job Finding Anxiety and AI Anxiety (r=.561). All subdimensions of AI Anxiety also demonstrated significant positive correlations with Job Finding Anxiety for example, Job Displacement (r=.491) and Sociotechnical Blindness (r=.496).

In addition, significant correlations were observed between Job Finding Anxiety and the subdimensions of AI Attitudes. The relationship between Job Finding Anxiety and Negative AI Attitudes was moderate and positive (r=.415), while a weaker, yet significant, correlation was found with Positive AI Attitudes (r=.288).

H2a: Job Finding Anxiety is significantly higher in females than in males.

An independent samples t-test was conducted to examine whether there were significant differences between female and male students in terms of AI Anxiety, AI Attitudes, and Job Finding Anxiety. The results of this analysis are presented in Table 3. To evaluate the magnitude of the significant differences, d values were calculated, as illustrated in Figure 4.

Table 3. Independent samples *t*-test results by gender.

	t	df	p	MD	SEdiff
Job Finding Anxiety	8.579	1055	<.001*	.462	.053
AI Anxiety	8.173	1055	<.001*	.687	.084
AI Attitudes	5.446	1055	<.001*	.286	.052
Incompetence Anxiety	7.070	1055	<.001*	.442	.062
Proximity Anxiety	8.235	1055	<.001*	.562	.068
Discrimination Anxiety	5.715	1055	<.001*	.328	.057
Country Conditions Anxiety	7.637	1055	<.001*	.490	.064
Negative AI Attitudes	8.057	1055	<.001*	.501	.062
Positive AI Attitudes	0.258	1055	.797	-.015	.061
Learning	4.351	1055	<.001*	.374	.086
Job Displacement	8.542	1055	<.001*	.878	.102
Sociotechnical Blindness	7.553	1055	<.001*	.790	.104
Configuration	9.005	1055	<.001*	1.0023	.111

As can be seen from Table 3, statistically significant differences were found in students' genders of AI Anxiety, AI Attitudes and Job Finding Anxiety. The table also presents the factors and subdimensions for which gender-based differences in mean scores were found to be significant. However, no significant difference was observed between female and male students in terms of Positive AI Attitudes.

Cohen's *d* (*d*) was calculated to determine the effect sizes. According to Cohen's (1988) classification, *d*=.20 indicates a small effect, *d*=.50 a medium effect, and *d*=.80 a large effect. Accordingly, the interpretation of the results considered not only statistical significance but also the magnitude of the observed effects.

Figure 4 displays the effect size values for the scales and subdimensions where significant mean score differences by gender were identified.

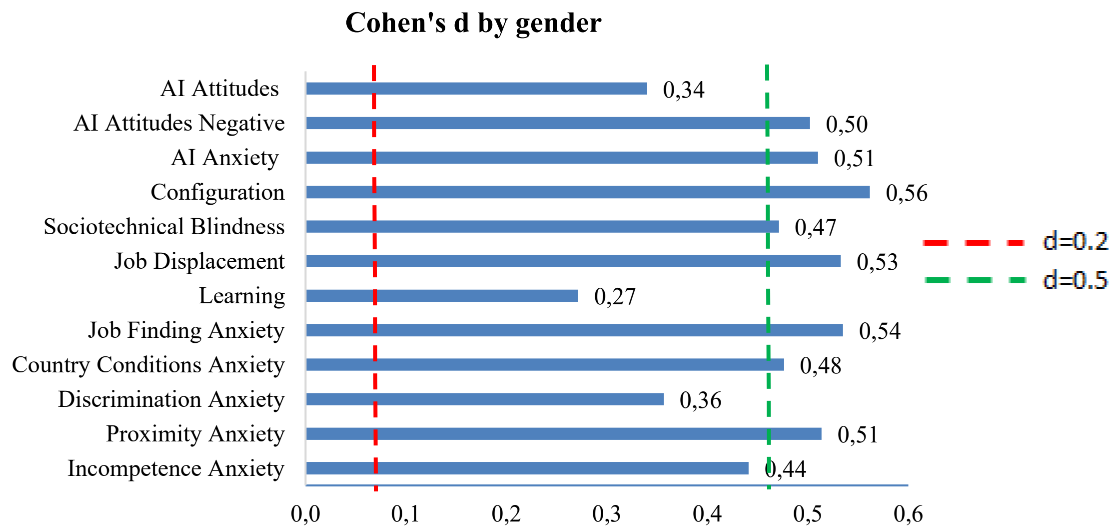


Figure 4. Gender-based Cohen's d effect sizes for scales and subfactors.

As shown in Figure 4, Job Finding Anxiety showed the largest gender-based difference. A moderate effect size in favor of female students was observed, with a *d*=.54. When analyzing the subdimensions, the Discrimination Anxiety subdimension of the Job Finding Anxiety yielded a *d*=.36, indicating that female students experience greater concern about potential discrimination in the labor market after graduation compared to their male counterparts. Furthermore, as shown in Table 1, female students obtained higher average scores in other subdimensions of Job Finding Anxiety, such as Country Conditions Anxiety and Incompetence Anxiety, suggesting that they may be more affected by systemic and structural factors during the transition to employment.

H2b: AI Anxiety is significantly higher in females than in males.

A similar gender based difference was also observed in variables related to AI. As shown in Figure 4, the effect size for the Negative AI Attitudes was *d*=.50, indicating that female students hold more Negative AI Attitudes than their male counterparts. Likewise, gender differences exceeding the medium effect size threshold were identified for the AI Anxiety and several of its subdimensions, including Configuration (*d*=.56), Sociotechnical Blindness (*d*=.47), and Job Displacement (*d*=.53). Table 1 also shows that females' AI Anxiety average scores are higher than males' in the Configuration, Sociotechnical Blindness, and Job Displacement subdimensions.

H3: There is a difference between academic year levels in terms of Job Finding Anxiety

ANOVA was conducted to determine whether university students differed significantly in their levels of AI Anxiety, AI Attitudes, and Job Finding Anxiety, as well as their related subdimensions, based on academic year (1st to 4th year). The results of the analysis are presented in Table 4.

Table 4. ANOVA table of scale scores by academic year.

		SS	df	MS	F	p
AI Anxiety	Between Groups	9.840	3	3.280	1.700	.165
	Within Groups	2031.235	1053	1.929		
	Total	2041.075	1056			
AI Attitudes	Between Groups	1.212	3	.404	.554	.646
	Within Groups	767.959	1053	.729		
	Total	769.171	1056			
Job Finding Anxiety	Between Groups	9.022	3	3.007	3.794	.010*
	Within Groups	834.673	1053	.793		
	Total	843.695	1056			
Incompetence Anxiety	Between Groups	8.672	3	2.891	2.757	.041*
	Within Groups	1104.003	1053	1.048		
	Total	1112.675	1056			
Proximity Anxiety	Between Groups	16.089	3	5.363	4.238	.005*
	Within Groups	1332.469	1053	1.265		
	Total	1348.558	1056			
Discrimination Anxiety	Between Groups	5.603	3	1.868	2.147	.093
	Within Groups	916.123	1053	.870		
	Total	921.727	1056			
Country Conditions Anxiety	Between Groups	9.641	3	3.214	2.892	.054
	Within Groups	1170.102	1053	1.111		

	Total	1179.743	1056			
Negative AI Attitudes	Between Groups	7.516	3	2.505	2.381	.068
	Within Groups	1108.050	1053	1.052		
	Total	1115.566	1056			
Positive AI Attitudes	Between Groups	1.466	3	89	.510	.675
	Within Groups	1007.903	1053	0.957		
	Total	1009.369	1056			
Learning	Between Groups	18.819	3	6.273	3.254	.021*
	Within Groups	2029.844	1053	1.928		
	Total	2048.663	1056			
Job Displacement	Between Groups	4.960	3	1.653	.568	.036*
	Within Groups	3063.839	1053	2.910		
	Total	3068.800	1056			
Sociotechnical Blindness	Between Groups	7.083	3	2.361	.796	.496
	Within Groups	3122.495	1053	2.965		
	Total	3129.578	1056			
Configuration	Between Groups	21.088	3	7.029	2.058	.104
	Within Groups	3596.056	1053	3.415		
	Total	3617.144	1056			

*:p≤.05

Eta squared (η^2) was used as a measure of effect size to indicate the proportion of total variance explained by the independent variable. According to Cohen's (1988) classification, values of $\eta^2<.01$ indicate a negligible effect, .01–.05 a small effect, .06-.13 a medium effect, and ≥.14 a large effect. As shown in Table 4 the null hypothesis of equal group means was rejected for certain scales and subdimensions ($p<.05$). Additionally, Cohen's *d* effect sizes were calculated for significant pairwise comparisons. The results of the Tukey HSD post hoc test indicated that second-year students had significantly higher scores on certain variables compared to students in other academic years.

Table 5. One-way ANOVA results and effect sizes by academic year.

Measurement	η^2	Academic Year	Academic Year	MD	p	*d*
Job Finding Anxiety	.010	1	2	-.197	.016*	-.22
Incompetence Anxiety	.007	1	2	-.197	.048*	-.19
Proximity Anxiety	.011	1	2	-.241	.021*	-.21
Proximity Anxiety	.011	2	3	.254	.026*	.22
Learning	.009	1	2	-.321	.023*	-.21
Job Displacement	.009	1	2	-.111	.012*	-.22

*:p≤.05

Across the Job Finding Anxiety scale, second year students reported significantly higher anxiety levels than first-year students (*d*=–.22). This difference was particularly pronounced in two subdimensions. In the Incompetence Anxiety subfactor, second year students exhibited higher levels of inadequacy related anxiety compared to first year students (*d*=–.19). Similarly, in the Proximity Anxiety subfactor, second year students reported significantly greater anxiety related to immediate environmental pressure than third year students (*d*=.23).

Regarding the AI Anxiety scale, second year students demonstrated significantly higher anxiety than first-year students in both the Learning subfactor (*d*=–.21) and the Job Displacement subfactor (*d*=–.22). In both dimensions, anxiety levels tended to increase with academic year.

Overall, the eta squared values for the comparisons ranged from .007 to .011, indicating small effect sizes. Although the proportion of variance explained is limited, these findings are not statistically negligible. They suggest that second-year students experience greater anxiety related to professional uncertainty, perceived competence, and the impact of technological change.

H4: Job Finding Anxiety is significantly lower in students studying in natural and applied field.

An independent samples *t*-test was conducted to examine whether students' levels of AI Anxiety, AI Attitudes, and Job Finding Anxiety significantly differed by field of study (i.e., social sciences/verbal fields vs. natural and applied fields). The results of the analysis are presented in Table 6.

Table 6. Independent samples t-test results by field.

	t	df	p	MD	SEdiff
AI Anxiety	2.89	1055	.004*	.249	.086
AI Attitudes	1,05	1055	.296	.055	.053
Job Finding Anxiety	4.08	1055	<.001*	.225	.055
Incompetence Anxiety	2.87	1055	.004*	.182	.063
Proximity Anxiety	3.53	1055	<.001*	.247	.070
Discrimination Anxiety	4.3	1055	< .001*	.247	.057
Country Conditions Anxiety	3.5	1055	<.001*	.229	.065
Negative AI Attitudes	2.37	1055	.018*	.151	.063
Positive AI Attitudes	-1.29	1055	.196	-.078	.060
Learning	1.5	1055	.135	.129	.086
Job Displacement	2.87	1055	.004*	.303	.105
Sociotechnical Blindness	3.03	1055	.003*	.323	.106
Configuration	3.16	1055	.002*	.362	.114

*:p≤.05

In terms of AI Anxiety, students in the social sciences reported significantly higher anxiety levels (M= 3.459; see Table 1) than their counterparts in natural and applied fields (M=3.210). This difference was particularly pronounced in the subdimensions of Job Displacement (*t*=2.87*), Sociotechnical Blindness (*t* =3.03*), and Configuration (*t*=3.16*). However, no statistically significant difference was found in the Learning subdimension of the AI Anxiety.

While no significant difference was observed in the total AI Attitudes score (*t*=1.05), a significant difference emerged in the Negative AI Attitudes subdimension (*t*=2.37*), indicating that students in social sciences reported more Negative AI Attitudes. In contrast, the Positive AI Attitudes dimension did not differ significantly between the groups (*t*=–1.29).

Regarding Job Finding Anxiety, students from the social sciences reported significantly higher anxiety levels compared to students in natural and applied fields (*t* =4.08*). This difference was statistically significant across all Job Finding Anxiety subdimensions: Incompetence Anxiety (*t*=2.87*), Proximity Anxiety (*t*=3.53*), Discrimination Anxiety (*t*=4.30*), and Country Conditions Anxiety (*t*=3.50*).

To assess the magnitude of these differences, effect sizes were calculated using Cohen's *d*. The results were visualized in Figure 5, which displays the effect sizes for each scale and subdimension showing significant group differences.

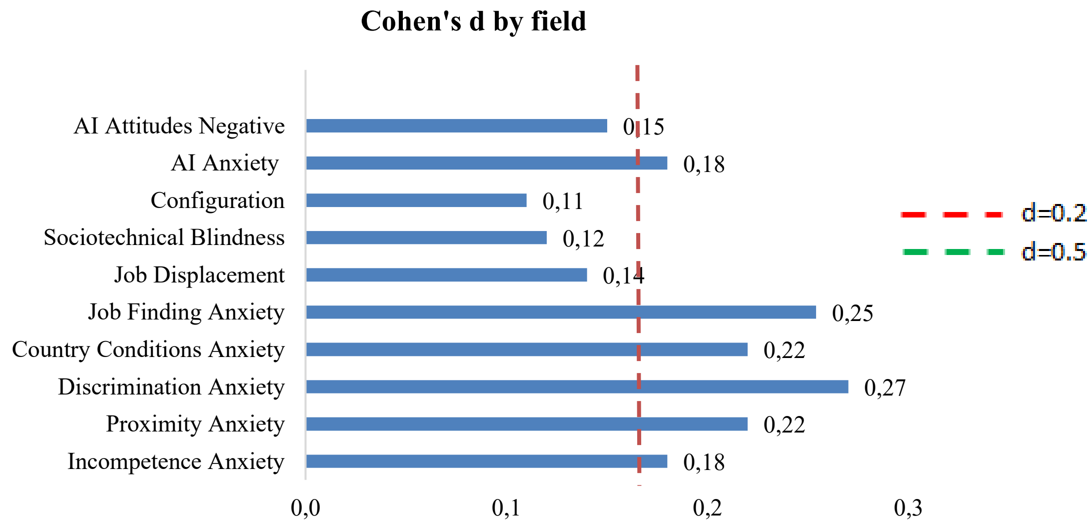


Figure 5. Cohen's *d* effect sizes by field of study across scales and subdimensions.

Overall, the findings indicate that students in the social sciences report higher levels of AI Anxiety and Job Finding Anxiety compared to students in natural and applied fields. However, the effect sizes of these differences are generally small, with most *d* values falling below .30.

When the total scores of the Job Finding Anxiety scale were examined, it was found that students in the social sciences had significantly higher average scores than those in natural and applied fields ($p<.05$); however, this difference corresponded to a small effect size ($d=.25$). At the subdimension level, social science students also scored significantly higher on the Proximity Anxiety and Country Conditions Anxiety subdimensions, with small effect sizes (both d =.22). The largest effect size was observed in the Discrimination Anxiety subdimension ($d=.27$), suggesting that students in the social sciences experience more intense concerns about facing discrimination in the labor market after graduation.

As shown in Figure 5, a similar trend was observed in the variables related to AI Anxiety. Students in the social sciences reported significantly higher anxiety levels than those in natural and applied fields, both on the overall AI Anxiety and on specific subdimensions such as Configuration, Sociotechnical Blindness, and Job Displacement. However, although these differences were statistically significant, the effect sizes remained small across all comparisons (e.g., AI Anxiety score=.18; Configuration=.11; Sociotechnical Blindness=.12; Job Displacement=.14). Similarly, social science students exhibited more Negative AI Attitudes subdimension; yet, the effect size was also small ($d=.15$), indicating that the observed differences, while statistically meaningful, were limited in practical significance.

Conclusions and Discussion

The findings show that students' concerns and attitudes toward AI have a significant impact on their Job Finding Anxiety after graduation, indicating that professional uncertainty is closely tied to emotional responses toward emerging technologies. Within the SCCT framework (Lent et al., 1994), this result highlights that career expectations are shaped by cognitive and emotional factors such as self efficacy, personal experiences, and environmental influences. According to SCCT, career expectations are shaped by environmental factors, self efficacy, personal experiences, and related cognitive-emotional processes. In this sense, concerns and negative attitudes toward technologies like AI can influence students' perceptions of their future careers. The moderate positive correlation between AI Anxiety and Job Finding Anxiety supports this, showing that technological anxiety is closely tied to career uncertainty. This aligns with recent work; for instance, Li et al. (2025) found that Chinese university students worried about AI's impact on the labor market perceived lower career security after graduation. Similarly, Albino et al. (2025) found that high perceived AI competence increases professional security, while low competence and negative attitudes heighten anxiety. Within the TAM framework (Davis, 1989), this suggests that perceptions of usefulness and ease of use shape attitudes and intentions toward technology. The significant link between Negative AI Attitudes and Job Finding Anxiety supports this view, showing that negative attitudes reduce acceptance and raise anxiety. The weak relationship between Positive AI Attitudes and Job Finding Anxiety further indicates that negative emotions may have a stronger impact. Yet, findings from studies in other contexts differ from these results. For instance, Köse (2025) found only a weak link between AI Anxiety and Job Finding Anxiety among accounting students, while the relationship was not significant in teacher education. These variations suggest that anxiety may differ by discipline, labor market expectations, and technological readiness. Overall, the results show that emotional responses to technological change are tied not only to cognitive acceptance but also to perceptions of job security and broader social conditions. This highlights the need to strengthen technological integration in education and provide psychological support for students during this transition.

Analyses for the second hypothesis showed that female students reported higher AI Anxiety and Job Finding Anxiety than male students and also had more Negative AI Attitudes. Cohen's d values indicate that these differences are both statistically and practically meaningful. These findings are particularly important when considered within social role theory (Eagly & Wood, 2012) and gender based career development models. Social role theory suggests that female, historically linked to care-oriented and low-risk professions, may reel greater uncertainty and loss of control during technological change. Female students' heightened sensitivity and anxiety about AI's impact on work may stem from gender norms and job insecurity (İlhan, 2025). Similar findings appear in recent studies. For instance, Migdadi et al. (2024), in a study conducted with nursing students, found that female students reported significantly higher AI Anxiety scores than their male counterparts, and that this anxiety was closely related to professional uncertainty. Similarly, Morales-García et al. (2025) reported that female students in Peru showed stronger negative emotional reactions and feelings of insecurity toward AI. The study also showed that women feel greater discrimination and inequality in job searches, and that technological change further deepens their already vulnerable position in the labor market. In this study, female students' higher scores on Discrimination Anxiety, Country Conditions Anxiety, and Incompetence Anxiety show how social and economic structures shape women's employment experiences, consistent with research on structural inequalities and the "glass ceiling" effect (OECD, 2023).

The findings revealed significant differences in Job Finding Anxiety and AI Anxiety across academic year levels. Second year students showed higher overall anxiety and higher scores on sub-dimensions such as Incompetence Anxiety, Proximity Anxiety, Learning, and Job Displacement than other groups. This suggests that second year students, still shaping academic identity and career goals, may be more vulnerable to uncertainty due to limited skills and experience. This aligns with Super's Lifespan Career Development Theory (1980), which states that individuals in early "exploration" and "trial" stages often experience career related uncertainty and conflict. Within this framework, second year students are at a stage where their "professional self concept" is forming, yet they lack practical experience and a sense of control. As a result, technological change and employment processes may feel more intense during this period. This can also be explained by Lazarus and Folkman's (1984) cognitive appraisal theory, which states that anxiety arises when individuals view a situation as threatening and believe they lack the resources to cope. High AI Anxiety and Job Finding Anxiety scores suggest that students perceive technological change as an "unmanageable threat," indicating a developmental disruption among second year students. Similarly, Liu et al. (2024) found that avoidance focused goals and anxiety increased in second and third years, and Karataş and Öktem (2022) reported that Job Finding Anxiety rose significantly during the middle years of study.

Çakır (2023) also stated that while career awareness grows at this stage, perceived lack of competence increases anxiety. Some studies, however, found no year level differences or reported higher anxiety among first year students. Tang et al. (2022) linked this to social adjustment and exam stress, and because this anxiety is temporary and not career oriented, it does not contradict the present findings. The rise in AI-related concerns across academic years suggests that students face limited knowledge, perceived skill gaps, and low awareness of employment risks. Insufficient understanding of AI's impact on learning and future jobs weakens self efficacy and increases fear of falling behind (Li et al., 2025). Thus, raising AI awareness, offering skill based training, and improving access to career counseling may help reduce these concerns.

Analyses for the fourth hypothesis revealed significant differences in AI Anxiety, AI Attitudes, and Job-Finding Anxiety across fields of study. Social science students scored higher on all measures, though with small effect sizes, suggesting they perceive greater professional risks from AI-driven change. Their higher scores in subdimensions like Discrimination Anxiety, Country Conditions Anxiety, and Proximity Anxiety indicate concerns not only about personal competence but also about structural and societal barriers to employment. This aligns with structural inequality theory (Feagin, 2012), which argues that some fields offer fewer opportunities and greater uncertainty. The same pattern emerges in AI Anxiety, as social science students appear more sensitive to AI's impact on the labor market, role changes, and perceived skill gaps. From an Expectancy-Value Theory perspective (Eccles & Wigfield, 2002), beliefs about future success may heighten emotional reactions to technological change. Overall, students in digital fields may view AI as an opportunity, while social science students tend to see it as a source of threat and uncertainty. Uçar et al. (2025) also reported a moderate link between AI Anxiety and Job-Finding Anxiety that varied by discipline and technological attitudes. Social science students felt less prepared for technological change and saw labor market competition as more threatening. These results support the present findings, suggesting that field differences stem not only from cognitive factors but also from social positioning and professional orientations.

Recommendations

The findings show that students' concerns and attitudes toward AI significantly influence Job Finding Anxiety. Thus, universities should offer programs that raise awareness of AI driven change, foster Positive AI Attitudes, and reduce anxiety. Integrating AI literacy, digital skill development, and technology focused career planning into coursework would be helpful. Since anxiety was higher among female and social science students, targeted support such as career counseling, psychosocial assistance, and skills based training should be prioritized for these groups. Higher anxiety among second year students highlights the need for early initiatives that support career orientation, digital adaptation, and labor market preparation. Policy level strategies should also address structural inequalities to reduce interdisciplinary gaps in career readiness. AI supported tools can enhance employability especially for social science students by expanding access to internships, project based learning, and structured mentoring. Future research could use methods like structural equation modeling and mixed method designs to explore causal relationships and better understand students' emotional responses to AI.

Declarations

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Informed Consent: *Every participant in the study provided their consent to engage in the data collecting process, and they were informed that they could cease participating at any moment. Every participant confirmed their consent.*

Data availability: *Data might be obtained from the author upon request.*

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