DEPARTMENT OF FINANCE AND BUSINESS ECONOMICS

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Artificial Intelligence's Influence on Job Security and Entrepreneurship

Project Work

By

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Submitted To:

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CERTIFICATE OF DECLARATION

This is to certify that the report entitled "**Artificial Intelligence's Influence on Job Security and Entrepreneurship**" which is submitted in partial fulfilment of the requirement for the award of degree of MBA (Business Economics) to the Department of Business Economics, South Campus, University of Delhi, comprises only my original work and due acknowledgment has been given in the text to all other materials used. This work has not been submitted/ published anywhere else.

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Prof. Chandar Mohan Negi

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I wish to express my appreciation to the numerous researchers whose work I referenced in the development of this project. Their contributions have enriched the content and provided essential context to my study. Proper acknowledgment has been given to them in the bibliography.

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EXECUTIVE SUMMARY

The proliferation of artificial intelligence (AI) has profound implications for the professional landscape, influencing job security perceptions and driving entrepreneurial pursuits. This study aimed to comprehensively analyze AI's intricate interplay with these pivotal aspects through a mixed-methods approach comprising surveys and advanced modeling techniques.

A comprehensive questionnaire was developed by integrating established scales measuring attitudes towards AI, entrepreneurial intentions, job insecurity, and technology adoption tendencies. The survey engaged 157 participants from diverse cohorts, including students, unemployed individuals, and employed professionals across various occupations. The data collection facilitated a nuanced understanding of perceptions across different demographic and occupational strata.

The study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) to explore AI attitudes, job insecurity, and entrepreneurial intentions. Findings revealed that negative attitudes towards AI (NAAI) significantly influenced job insecurity, while positive attitudes (PAAI) correlated with increased entrepreneurial intentions. Demographic factors like gender, education, income, and startup experience had varying effects, requiring tailored approaches.

The PLS-SEM model demonstrated moderate predictive relevance, offering a more accurate framework for forecasting AI's professional impacts. These insights deepen understanding of AI's influence on job security and entrepreneurship, guiding strategies for individuals and organizations navigating this evolving landscape.

The study fills a gap in empirical research, confirming AI perceptions' central role in shaping job insecurity and entrepreneurial intent. It underscores the complexity of factors influencing professional trajectories.

Recommendations include further theory development, enhancing model explainability, and improving predictive capabilities. These insights can inform policy, workforce development, and strategies for navigating the AI-driven professional landscape effectively.

By combining quantitative rigor with qualitative insights, this research offers a robust foundation for understanding AI's multifaceted influence on job security and entrepreneurship, guiding individuals, organizations, and policymakers in leveraging AI's potential while mitigating disruptions.

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1. Introduction

1.1 Background

Artificial Intelligence (AI) has a rich history dating back to the mid-20th century, with its roots in the development of intelligent machines that mimic human cognitive processes. Coined by John McCarthy in 1956, the concept of AI has undergone various phases of innovation, skepticism, and resurgence over the decades. These historical fluctuations, often referred to as AI winters, have been characterized by periods of high enthusiasm followed by disillusionment due to the limitations of technology at the time.

Recent advancements in computational power, the availability of vast amounts of big data, and breakthroughs in machine learning have led to a resurgence of interest in AI. This resurgence has propelled the integration of AI into diverse domains such as natural language processing, computer vision, and reinforcement learning. Key technologies like neural networks, deep learning architectures, and predictive analytics have played pivotal roles in leveraging AI capabilities. Moreover, innovations in autonomous systems, robotics, and the Internet of Things (IoT) have expanded AI's utility, enhancing its transformative potential across industries.

1.2 Relevance of the Study

Against this backdrop, there is a growing need to understand AI's intricate interplay with job security and entrepreneurial pursuits. While scholarly inquiries into AI's implications for employment stability and entrepreneurship have been abundant, prior analyses have often relied on derivative studies lacking direct empirical insights from diverse cohorts. Thus, there is a gap in the literature that this study seeks to address by providing comprehensive insights into individuals' perceptions across various occupational strata regarding AI's impact on employment and entrepreneurship.

1.3 Scope of the Study

This research aims to bridge this gap by employing a comprehensive survey-based methodology to gauge perceptions towards AI across different professional echelons and among students. By measuring attitudes towards AI, technology adoption tendencies, job security concerns, and entrepreneurial intentions, the study seeks to provide nuanced insights into the opportunities and challenges associated with AI's proliferation. Through a hybrid approach combining quantitative analysis and qualitative inquiries, the study intends to identify demographic divergences in AI perceptions and correlate these with levels of job-related anxiety and entrepreneurial drive. Ultimately, the study aims to offer empirically grounded insights to inform policy formulations and facilitate adept navigation within the evolving AI landscape across professional domains.

2. Literature Review

2.1 Background

Artificial Intelligence (AI) has emerged as a transformative force, tracing its origins back to the mid-20th century with the concept initially conceptualized by John McCarthy in 1956. Over the years, AI has experienced a series of fluctuations, characterized by phases of enthusiasm followed by skepticism, commonly referred to as AI winters. These historical cycles have been marked by periods of high expectations, subsequent disappointments due to technological limitations, and subsequent resurgence driven by advancements in computational power, data availability, and breakthroughs in machine learning.

2.2 Review

Public Attitudes towards AI:

Several studies delve into public attitudes towards AI, highlighting factors such as industry context, socio-cultural influences, and gender disparities. Vasiljeva et al. (2021) and Albarran Lozano et al. (2021) investigate attitudes towards AI in different industries and countries, identifying factors like top management's attitude and interest in technological developments as significant determinants.

Kim & Lee (2023) and Kelley et al. (2021) explore the influence of socio-cultural factors on attitudes towards AI among middle school students and across eight countries respectively. They reveal variations in attitudes based on factors like gender, AI-related experiences, and cultural contexts, providing nuanced insights into public perceptions of AI.

Schepman and Rodway (2020, 2022) developed and validated the General Attitudes towards Artificial Intelligence Scale (GAAIS). Their studies confirmed its two-factor structure (Positive, Negative) and identified individual psychological factors influencing attitudes towards AI, such as introversion, conscientiousness, and trust levels. These findings provide insights into the complexities of AI acceptance among individuals.

Measurement of Threat Perceptions:

Studies by Kieslich et al. (2020) and Nomura et al. (2006) focus on measuring threat perceptions associated with AI and robots. They propose scales such as the Threats of AI (TAI) scale and the Negative Attitudes toward Robots Scale (NARS) to assess threat perceptions across different domains and contexts.

Technology Acceptance:

Goswami and Dutta (2016) reviewed literature on gender disparities in technology usage. While gender's influence on technology acceptance varies across contexts, their study highlights the significance of considering gender perspectives in understanding technology usage patterns.

Marangunić & Granić (2015) offer a comprehensive review of the Technology Acceptance Model (TAM), highlighting its evolution and suggesting future research directions. Bruner et al. (2007) develop the Technology Adoption Scale (TAS) to measure consumers' propensity to adopt high-tech products, providing a validated tool for understanding consumer attitudes. Wang et al. (2021) empirically evaluate TAM for AI adoption in e-commerce, identifying factors like subjective norms and perceived usefulness that influence attitudes towards AI adoption.

Artificial Intelligence and Job Automation:

Peng & Bhaskar (2023) review the role of AI and machine learning in job automation, proposing an integrated framework for balancing job automatability with practical considerations. They emphasize the importance of employees acquiring analytical and interpersonal skills to thrive in automated workplaces, suggesting adaptations in educational curricula to meet workforce demands.

Fear of Automation:

Golin and Rauh (2022) and Presbitero and Teng-Calleja (2023) delve into the psychological ramifications of workers' perceptions of AI's threat to their jobs. Golin and Rauh's research uncovers a strong correlation between workers' perceived probability of job loss due to automation and their preferences for redistribution and participation in collective action such as joining a union. They find that heightened fear of automation often translates into support for policies aimed at redistributing wealth, such as higher taxation and increased government handouts. Moreover, they reveal a notable impact on career behaviors, with workers more inclined towards exploring alternative career paths in response to perceived job insecurity induced by AI advancements. Presbitero and Teng-Calleja (2023) build upon this by demonstrating that employees' perceptions of AI taking over their jobs influence their career exploration behaviors. They identify job insecurity and psychological distress as mediating factors, suggesting that concerns about AI-driven job displacement not only affect workers' economic attitudes but also shape their career decision-making processes.

Relationship Between Job Anxieties and Social Relations:

Srivastava (1977) contributes to our understanding of the psychological implications of job anxieties on employees' social relations and adjustment. Through their study, Srivastava establishes a link between employees' anxieties regarding various aspects of their job and their social interactions and adjustment outside of the workplace. They hypothesize that job anxieties, including concerns about job security and satisfaction, negatively impact employees' participation in social activities and their attitudes towards community members. This insight underscores the broader societal consequences of job-related stressors, emphasizing the need for organizations and policymakers to address not only the economic but also the social dimensions of AI-induced workplace transformations.

Implementation of AI for Business Model Innovation:

Reim et al. (2020) and Thommie Burström et al. (2021) provide guidance on leveraging AI for business model innovation (BMI). Reim et al. offer a roadmap for implementing AI in firms, emphasizing the need to understand AI capabilities and organizational readiness. Meanwhile, Thommie Burström et al. explore how manufacturing incumbents integrate AI into their business models, highlighting the importance of aligning AI-enabled innovation with ecosystem dynamics.

Hou et al. (2019) and Valliere (2015) delve into the factors shaping entrepreneurial intention. Hou et al. construct an integrated model incorporating variables like entrepreneurial passion and self-efficacy, providing insights into how these factors influence entrepreneurial intention among university students. Valliere proposes the Entrepreneuring Intent Scale, offering a more accurate measure of entrepreneurial intent by distinguishing it from related constructs.

Methodology Selection:

Regmi et al. (2016) highlight the advantages of online questionnaire surveys, emphasizing their cost-effectiveness and efficiency in data collection, especially for sensitive topics or hard-to-reach populations. They provide guidance on methodological aspects, survey planning, and ethical considerations, aiding researchers in utilizing online surveys effectively.

Dash and Paul (2021), Hair et al. (2017), and Hair et al. (2011) compare covariance-based structural equation modeling (CB-SEM) with partial least squares structural equation modeling (PLS-SEM). They discuss the differences in these methods and their suitability for various research contexts, providing empirical evidence and guidelines for researchers to choose the most appropriate SEM approach.

Ramli et al. (2018) and Willaby et al. (2015) explore the application of partial least squares structural equation modeling (PLS-SEM) in research contexts. Ramli et al. (2018) examine its effectiveness in analyzing capital structure determinants, while Willaby et al. (2015) demonstrate its utility in testing complex models with small sample sizes, particularly in differential psychology research. Their findings underscore the advantages of PLS-SEM in specific research scenarios.

This synthesized literature review provides a concise overview of existing scholarship, elucidating the intricate interplay between AI acceptance, labor market dynamics, fear of automation, entrepreneurial endeavors, and ethical considerations.

2.3 Research Gaps

The synthesized literature identifies critical research gaps that warrant further exploration within the realm of AI's influence on job security, entrepreneurial intentions, emotional reactions, and ethical considerations:

1. **Comparative Analysis**: Existing research lacks comparative analyses between students, unemployed, and employed groups concerning AI's impact on job security and entrepreneurial prospects, hindering a nuanced understanding of diverse perceptions (Aghion et al., 2019; Zarifhonarvar, 2023).

2. **Reliance on Secondary Data**: Many studies predominantly rely on secondary data concerning occupation-level automation risks rather than directly measuring first-hand perceptions of AI's impact, creating a gap in understanding individuals' direct sentiments (Bonfiglioli et al., 2023; Zarifhonarvar, 2023).

3. **Role of Demographic Factors**: Further exploration into the role of demographic factors such as age, education, and gender in shaping AI attitudes is necessary to unveil nuanced perceptions (Albarran-Lozano et al., 2021; Marangunić & Granić, 2015).

4. **Incorporation of AI Factors in Entrepreneurial Intentions**: Studies on entrepreneurial intentions would benefit from incorporating AI-related factors like awareness and automation risk perceptions for a more holistic understanding (Hou et al., 2019; Valliere, 2015).

5. **Exploration of Emotional Reactions**: Research exploring emotional reactions, particularly anxiety about AI, remains limited and necessitates further investigation for a comprehensive understanding (Kieslich et al., 2020; Golin & Rauh, 2022).

3. Objectives and Hypotheses

3.1 Objectives

1. Analyze the Impact of AI on Job Security: Investigate how AI influences perceptions of job security and assess its economic implications.

2. Analyze the Impact of AI on Entrepreneurial Intent: Examine how AI affects entrepreneurial intentions and its role in shaping economic dynamics.

3. Explore Demographics with Latent Variables: Investigate the interactions between demographic factors and attitudes towards AI using latent variable analysis.

4. Help Formulate the Steps Ahead: Provide actionable insights and recommendations based on research findings to guide future policies and strategies in response to AI's impact on job security, entrepreneurial endeavors, and demographic variations.

3.2 Hypothesis Development

Direct Effects Hypotheses:
H1: PAAIS → TA (Positive Attitude towards AI has a direct positive effect on Technology Acceptance)

H2: NAAIS → JS (Negative Attitude towards AI has a direct positive effect on Job Insecurity)

H3: TA → EI (Technology Acceptance has a direct positive effect on Entrepreneurial Intent)

Indirect Effects Hypotheses:
H4: PAAIS → TA → EI (Positive Attitude towards AI has an indirect positive effect on Entrepreneurial Intent through its effect on Technology Acceptance)

H5: NAAIS → TA → JS → EI (Negative Attitude towards AI has an indirect positive effect on Entrepreneurial Intent through its effects on Technology Acceptance and Job Insecurity)

In these hypotheses, the arrows (→) represent the hypothesized direct and indirect effects between the latent variables, using the following abbreviations:

PAAIS: Positive Attitude towards AI
NAAIS: Negative Attitude towards AI
TA: Technology Acceptance
EI: Entrepreneurial Intent
JS: Job Insecurity

4. Research Methodology

Questionnaire Development:
The questionnaire was developed by integrating scales identified in the literature review. It utilized both formative and reflective constructs to facilitate effective Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. Measures for assessing Positive and Negative Attitudes toward AI, Technology Acceptance, Job Insecurity, Entrepreneurial Intent, and demographic factors were included in the questionnaire.

Data Analysis:
The survey data underwent exploratory data analysis (EDA) to understand distributions across demographic factors. Bivariate and multivariate analyses were conducted to explore relationships between demographics and attitudes/intentions related to AI, job security, and entrepreneurship. Comparisons across demographic groups were made to identify differences in perceptions and behaviors. This informed subsequent analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM) to validate the model.

Model Specification and Validation:
Firstly, defining the research question and theoretical model was done. Then identifying latent constructs and their relationships while ensuring theoretical relevance and clarity in model conceptualization.
The following procedure was conducted for validating the model:

a. *Evaluate indicator loadings:* Indicators should load strongly on their respective latent constructs.
b. *Assess composite reliability:* Ensure internal consistency of constructs.
c. *Calculate average variance extracted (AVE):* Verify convergent validity of constructs.

Model Construction:
Based on the survey findings and data analysis, the final structural model was constructed. This model depicted the relationships between latent variables and demographic factors.
The following steps were followed in evaluating the model:

a. *Evaluate path coefficients:* Assess the significance and direction of relationships between latent constructs.
b. *Test predictive relevance:* Evaluate the effect sizes and predictive relevance of the structural paths.
c. *Conduct bootstrapping:* Use bootstrapping procedures to estimate standard errors, confidence intervals, and p-values for path coefficients.

5. Data Sources and Description

5.1 Primary Data Collection

5.1.1 Sample

The primary data for this study was obtained through a survey conducted among respondents. A total of 201 survey responses were collected. To ensure data quality, attention checks were incorporated, particularly within the Job Insecurity section of the questionnaire. Out of the 201 responses, 157 were deemed valid after filtering out responses that failed attention checks.

Despite the reduction in the number of valid responses due to attention checks, the remaining dataset still adhered to the 10x rule of Partial Least Squares Structural Equation Modeling (PLS-SEM). This rule suggests that the sample size should be at least 10 times the maximum number of inner model paths. Hence, the dataset was deemed suitable for analysis.

The questionnaire utilized in the survey was meticulously designed, incorporating scales identified in the literature review. Some scales were modified to align with the specific objectives of the study. These modifications aimed to ensure the questionnaire's relevance and effectiveness in capturing the desired constructs related to attitudes and intentions regarding AI, job security, and entrepreneurship.

5.1.2 Description of Variables

The survey includes demographic variables and attitudinal statements to assess respondents' perspectives on artificial intelligence (AI), job security, and entrepreneurial intentions. Please refer to Appendix 1 below for the questionnaire design and detail description of scales used.

Demographic Variables:
These variables capture respondents' personal characteristics such as age, gender, highest education level, occupation, years of work experience, startup experience, and last reported income level.

Attitudinal Statements:

1. **Positive Attitude towards AI (PAAIS)**: These statements gauge respondents' favorable views of AI. For example, attitudes towards using AI in daily life, belief in its positive impacts, excitement about AI, and willingness to adopt AI in their jobs.
2. **Negative Attitude towards AI (NAAIS)**: These statements assess respondents' concerns or negative perceptions of AI, such as its potential dangers, ethical issues, error-proneness, and adverse impacts on society and personal well-being.

3. **Entrepreneurial Intent (EI)**: These items measure respondents' intentions and motivations related to entrepreneurship, including their interest in using AI for business solutions, perceptions of AI's impact on startup barriers, determination to become entrepreneurs, and attitudes towards AI's influence on future entrepreneurship opportunities.
4. **Job Security (JS)**: These statements explore respondents' perceptions of job security in the context of AI, including beliefs about AI's impact on the job market, uncertainty about job futures due to AI, concerns about skill obsolescence, and worries about the importance of their jobs in the AI era.
5. **Technology Acceptance (TA)**: These items assess respondents' attitudes towards adopting AI-powered tools and technologies, including their willingness to use AI, active adoption of AI technologies, commitment to skill upgrading in AI-related areas, and criteria for adopting AI systems.

Optional Open-Ended Questions:
Respondents are given the opportunity to provide qualitative insights on the future impact of AI on entrepreneurship, jobs and careers, factors considered before adopting AI, and general feedback.

Global Items (GI) and Reverse-Coded Items:
Some items, denoted as "Global Items (GI)," serve as formative indicators in the measurement model. They are designed to influence the latent constructs directly rather than being influenced by them. These items include statements about the beneficial applications of AI and its dangers.

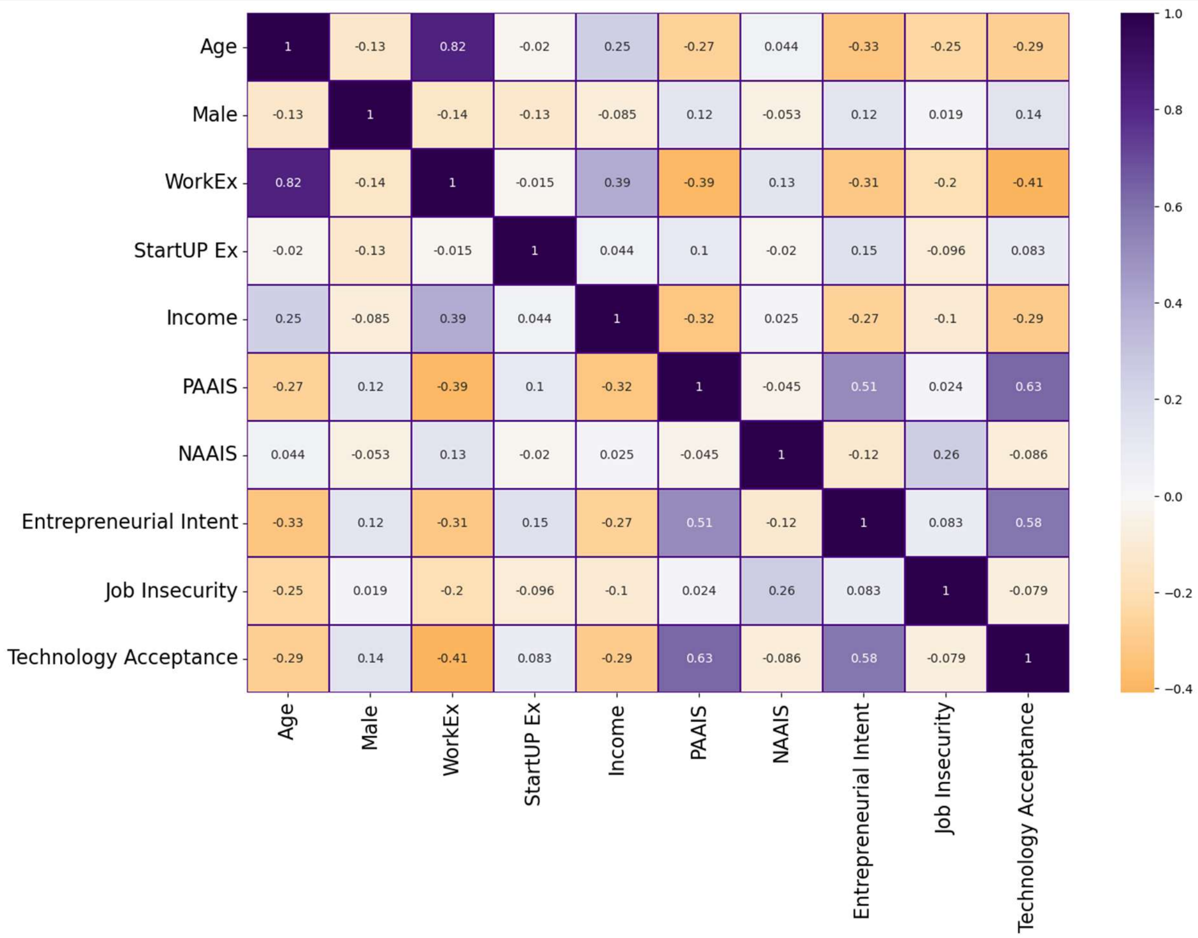
Additionally, some items are reverse-coded to counteract response bias and ensure more accurate measurement of constructs. For example, statements about AI making entrepreneurship seem hard or reducing the importance of certain jobs are reverse-coded to capture diverse perspectives.

6. Analysis and Results

6.1 Exploratory Data Analysis

1. The correlation matrix shows:
    a. Strong positive correlations between Age and Work Experience, as well as between Work Experience and Income.
    b. Moderate negative correlations between Age & Work Experience, and Positive Attitudes Toward AI (PAAIS).

Figure 1. Correlation Matrix



    c. Moderate positive correlations between PAAIS & Entrepreneurial Intent, and between PAAIS & Technology Acceptance.

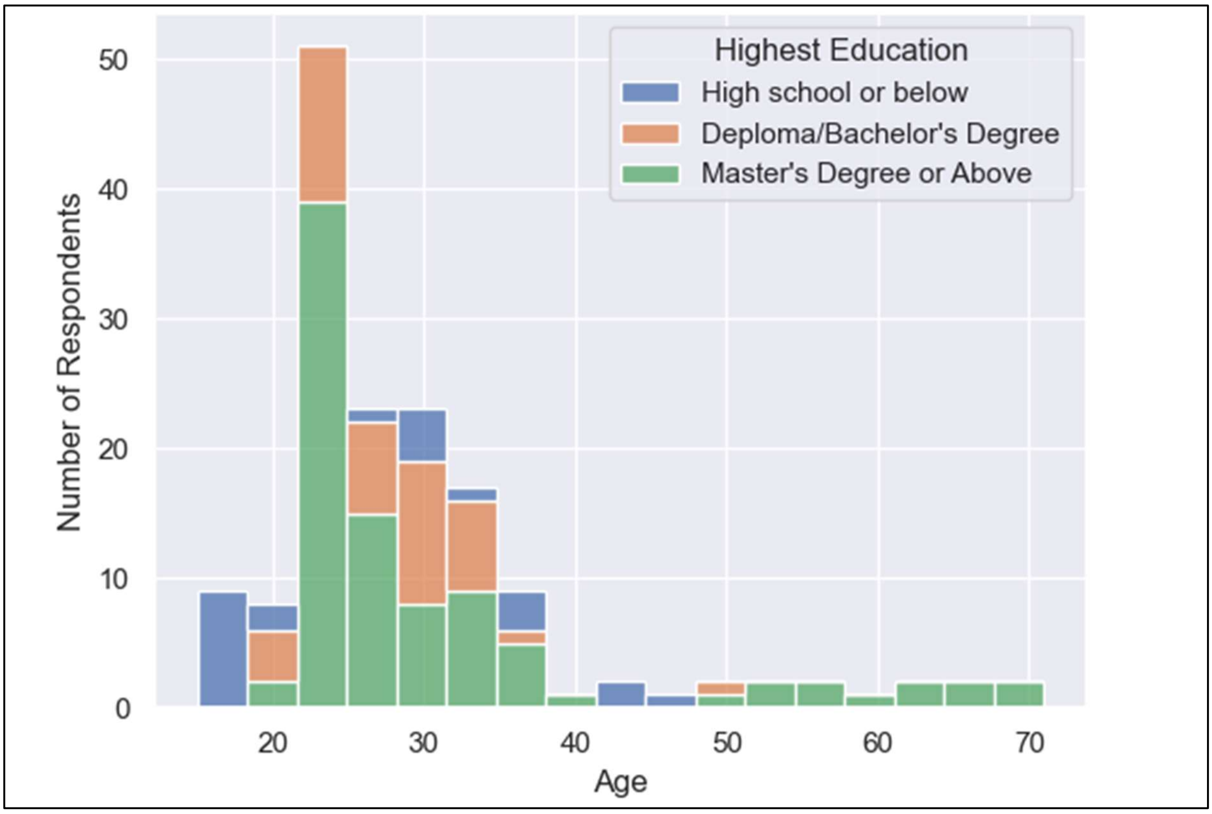
    d. There is a weak negative correlation between Age and Entrepreneurial Intent, as well as between Age and Job Insecurity.

e. Positive Attitudes Toward AI (PAAIS) exhibit a strong positive correlation with Entrepreneurial Intent and Technology Acceptance, while Negative Attitudes Toward AI (NAAIS) show weak correlations with other variables.

A scatterplot matrix for the scales has been included in Appendix 2 below.

2. This bar graph shows the distribution of respondents based on their age and the highest level of education they have attained. The x-axis represents the different age groups, while the y-axis shows the count or frequency of respondents.

Figure 2. Distribution of Respondents



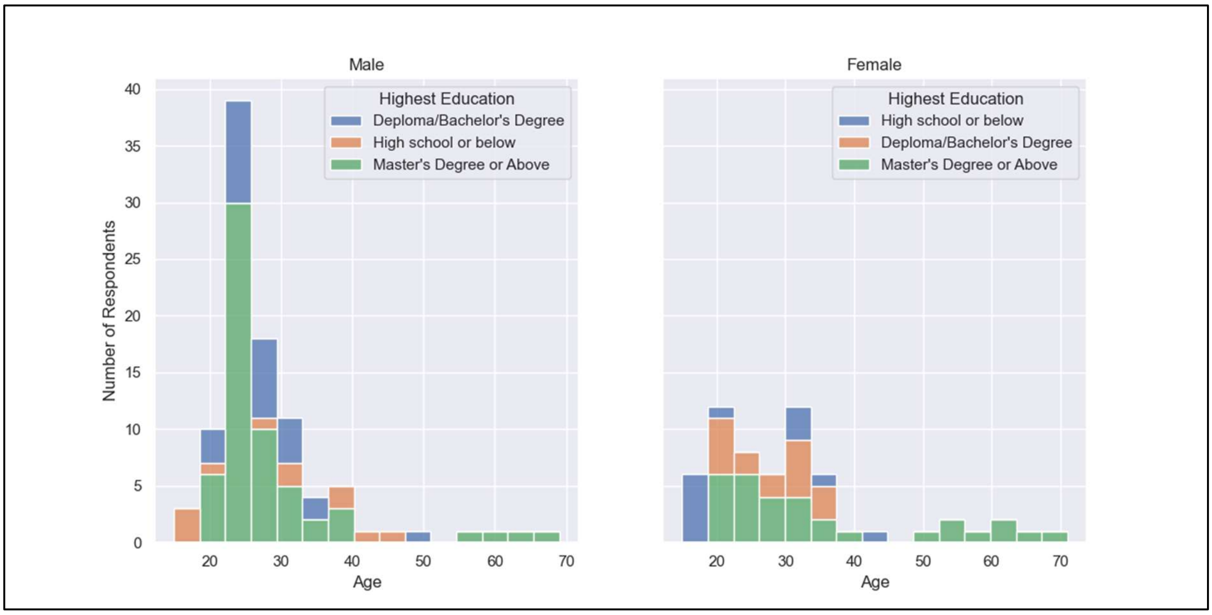
Each bar is divided into segments representing the various education levels, such as "High school or below," "Diploma/Bachelor's Degree," and "Master's Degree or Above." The height of each colored segment within a bar indicates the number of respondents in that particular age group with the corresponding education level.

Insight: Most respondents, particularly those below 30, hold diploma/bachelor's or master's degrees, with a concentration in the 20-30 age range, while older age groups are underrepresented.

3. These stacked bar charts further divides the distribution of respondents based on their gender.

Insight: In most age groups, male respondents outnumber females, with the highest participation seen among those aged 20-30, while older age groups have fewer respondents, regardless of gender. Additionally, there appears to be a higher number of respondents with a high school education or below among male age groups.

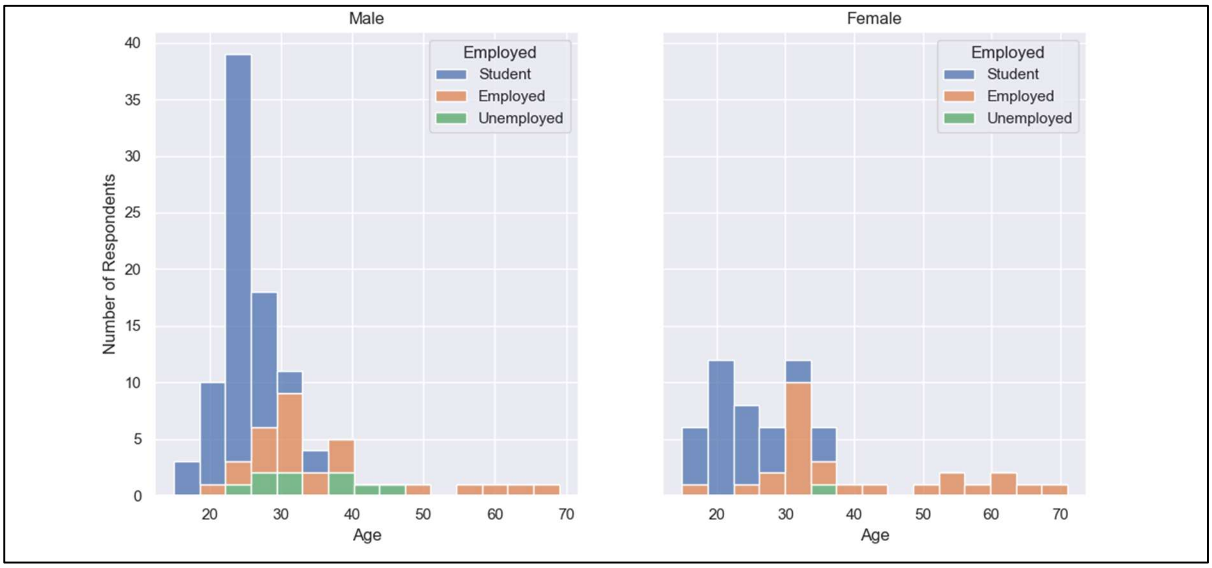
Figure 3. Distribution of Education for different Genders across Age



4. These stacked bar charts divides the distribution of respondents and their Employment Status based on their gender. Each bar corresponds to a specific employment status, and its height indicates the number of respondents belonging to that category.

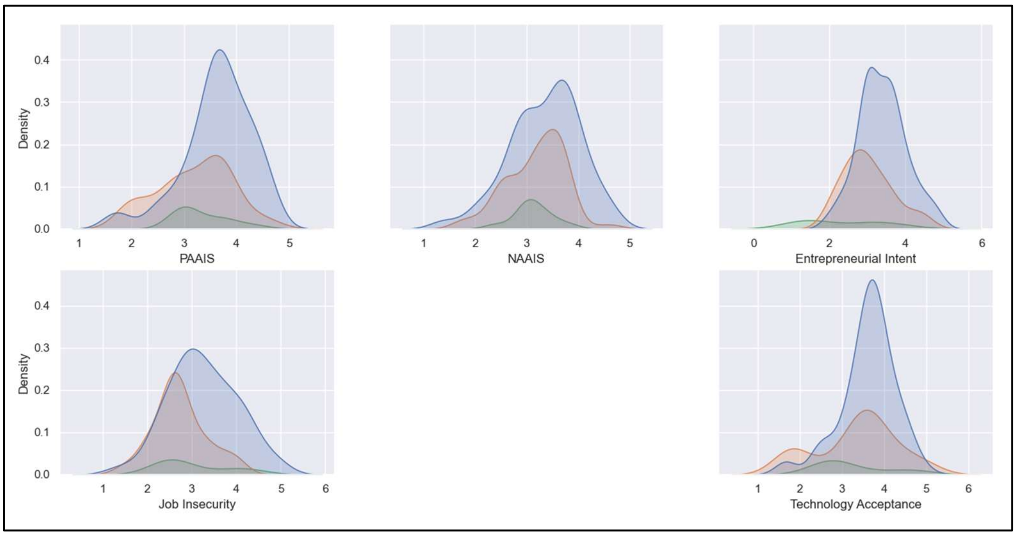
   Insight: Most respondents across genders are students, followed by employed individuals, with a notably lower representation of unemployed respondents, particularly among females.

Figure 4. Distribution of Employment for different Genders across Age



5. The following graphs illustrate the density of each latent variable based on the scale values and the employment level, revealing distinct distributions among students, employed individuals, and unemployed individuals.

Figure 5 Density Graph of Latent Variables on the Basis of Employment Status



The density distributions reveal nuanced insights across employment statuses:

a. Among students and employed individuals, positive attitudes toward AI (PAAIS) and entrepreneurial intent (EI) exhibit skewed distributions, indicating a polarized range of sentiments, from highly positive to somewhat reserved. Conversely, the unemployed show a more evenly distributed spectrum of attitudes towards AI.
b. Negative attitudes toward AI (NAAIS) are consistently skewed across students and employed individuals, suggesting a prevailing tendency towards skepticism or

caution. However, among the unemployed, there's a broader diversity of attitudes towards AI, with a relatively normal distribution.

c. Job insecurity appears to have a more uniform distribution across all employment statuses, indicating a varied perception of job stability regardless of employment status.

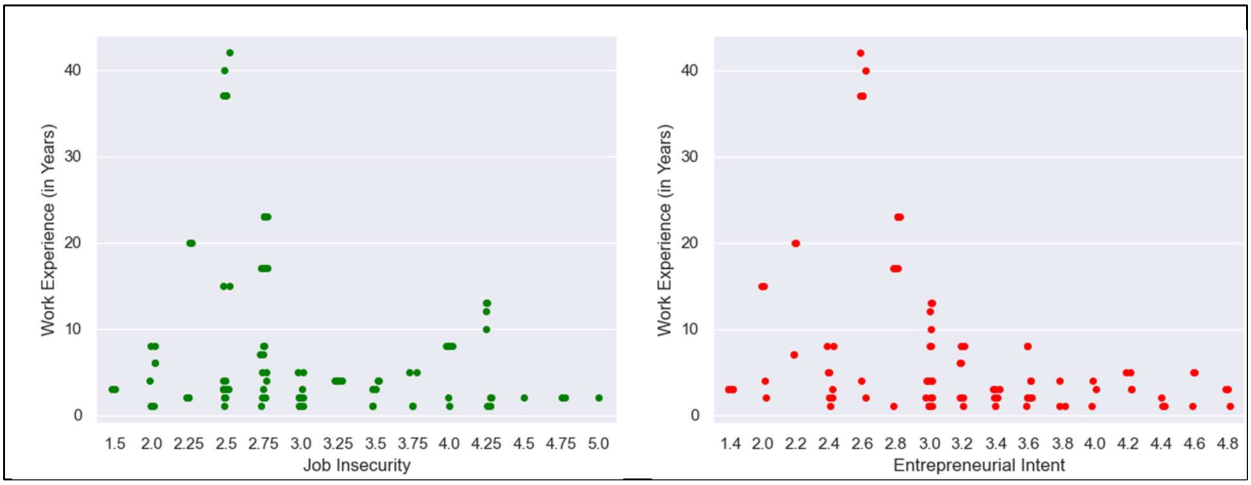
d. Technology acceptance (TA) shows a predominantly negative skew among both students and employed individuals, hinting at a general inclination towards adopting new technologies, albeit with some reservations or selectivity.

6. These two scatter plots examine the influence of Work Experience on Job Insecurity & Entrepreneurial Intent.

Insight:

a. Lower levels of work experience are associated with higher levels of both job insecurity and entrepreneurial intent, indicating a correlation between career uncertainty and entrepreneurial aspirations among early-career individuals.

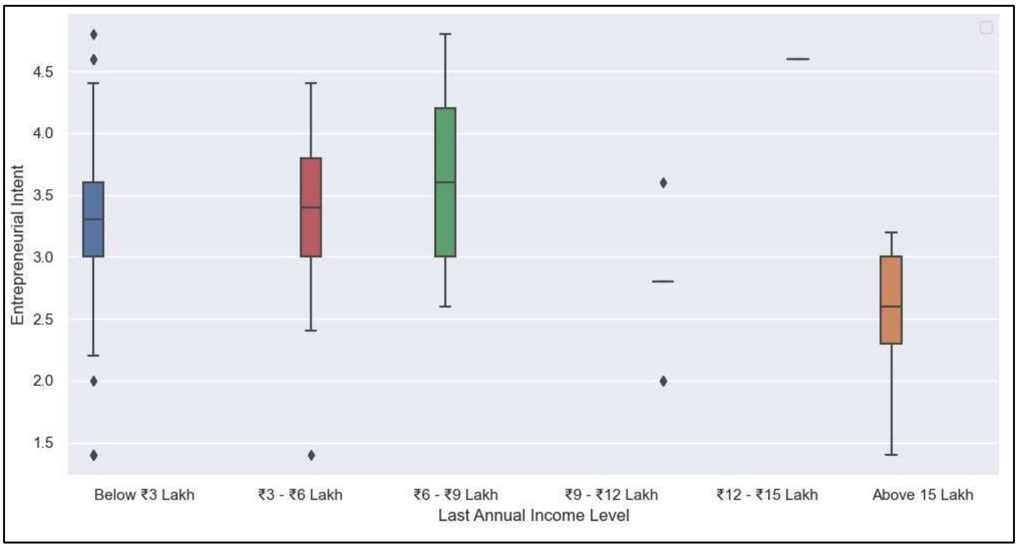
Figure 6 Work-Ex and Job Insecurity and Entrepreneurial Intent



b. Conversely, higher levels of work experience correspond to lower levels of both job insecurity and entrepreneurial intent, suggesting increased stability in both employment and entrepreneurial aspirations among more experienced individuals.

7. This plot displays the distribution of respondents' income levels on the x-axis and their Entrepreneurial Intent scores on the y-axis.

Figure 7. Income Level and Entrepreneurial Intent



Insights:

a. *Lower income levels display a broad range of entrepreneurial intent, indicating varied aspirations among individuals with limited financial resources.*

b. *Entrepreneurial intent tends to increase with rising income levels until reaching a peak at moderate income levels, after which it declines, suggesting a non-linear relationship between income and entrepreneurial aspirations.*

6.2 Structural Modal Equation Formation

6.2.1 Formative Model

The following procedure was followed for validating the Reflective Models:

i. Variance Inflation Factor (VIF) values were assessed to detect multicollinearity, ensuring values remained below 5.

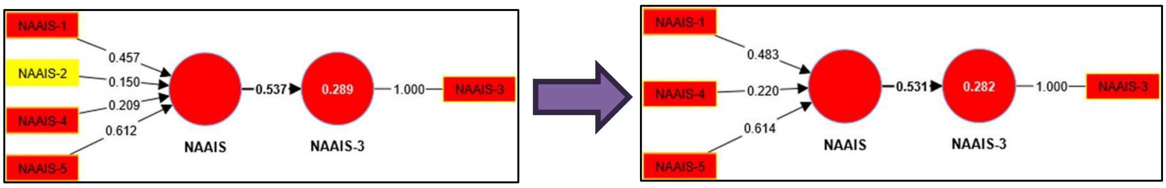
ii. Path coefficients between formative indicators and their respective constructs were examined, retaining indicators with coefficients surpassing 0.7. If not satisfied then:

   a. The significance of outer weights was determined through p-values and confidence intervals, with insignificant weights prompting inspection of outer loadings as per the following:

      i. Indicators were retained if their mean outer loading exceeded 0.5 and exhibited significant p-values.

NAAIS

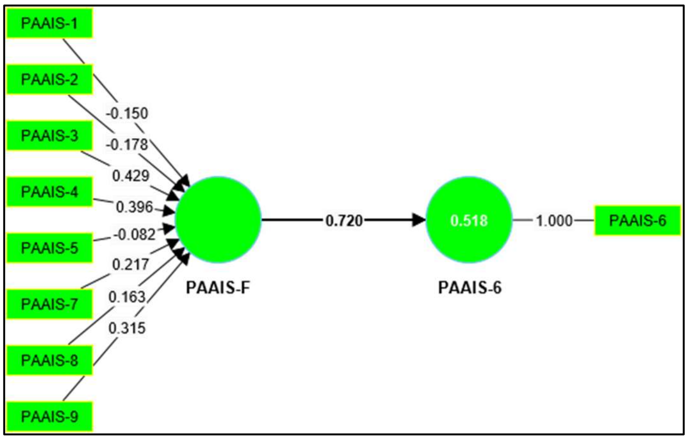
Figure 8 NAAIS Formative Model



NAAIS-3 was used as a Global Item for the Formative Model for NAAIS. NAAIS-2 did not meet the specified criterion as outlined earlier, so it was eliminated from the model and the tests were conducted again and the updated model was satisfying the conditions.

PAAIS

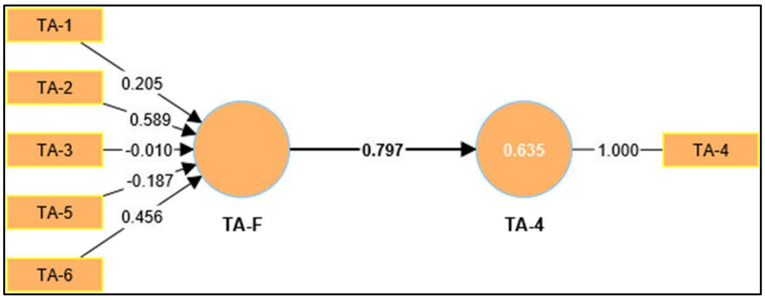
Figure 9. PAAIS Formative Model



PAAIS-6 was used as a Global Item for the Formative Model for PAAIS. All the items met the specified criterion as outlined earlier, so none were eliminated from the model and the model was finalized for further analysis.

Technology Acceptance

Figure 10. Technology Acceptance Formative Model



TA-4 was used as a Global Item for the Formative Model for Technology Acceptance Model. All the items met the specified criterion as outlined earlier, so none were eliminated from the model and the model was finalized for further analysis.

6.2.2 SEM Formation

After removing items like EI-3 and JS-1 due to their low Outer Loadings and considering the insufficient Cronbach's Alpha and Average Variance Extracted for Entrepreneurial Intent and Job Insecurity, the finalized model was established for subsequent evaluation. Refer to the Appendix 2 below for Reflective Model Testing.

Figure 11. Reflective Model

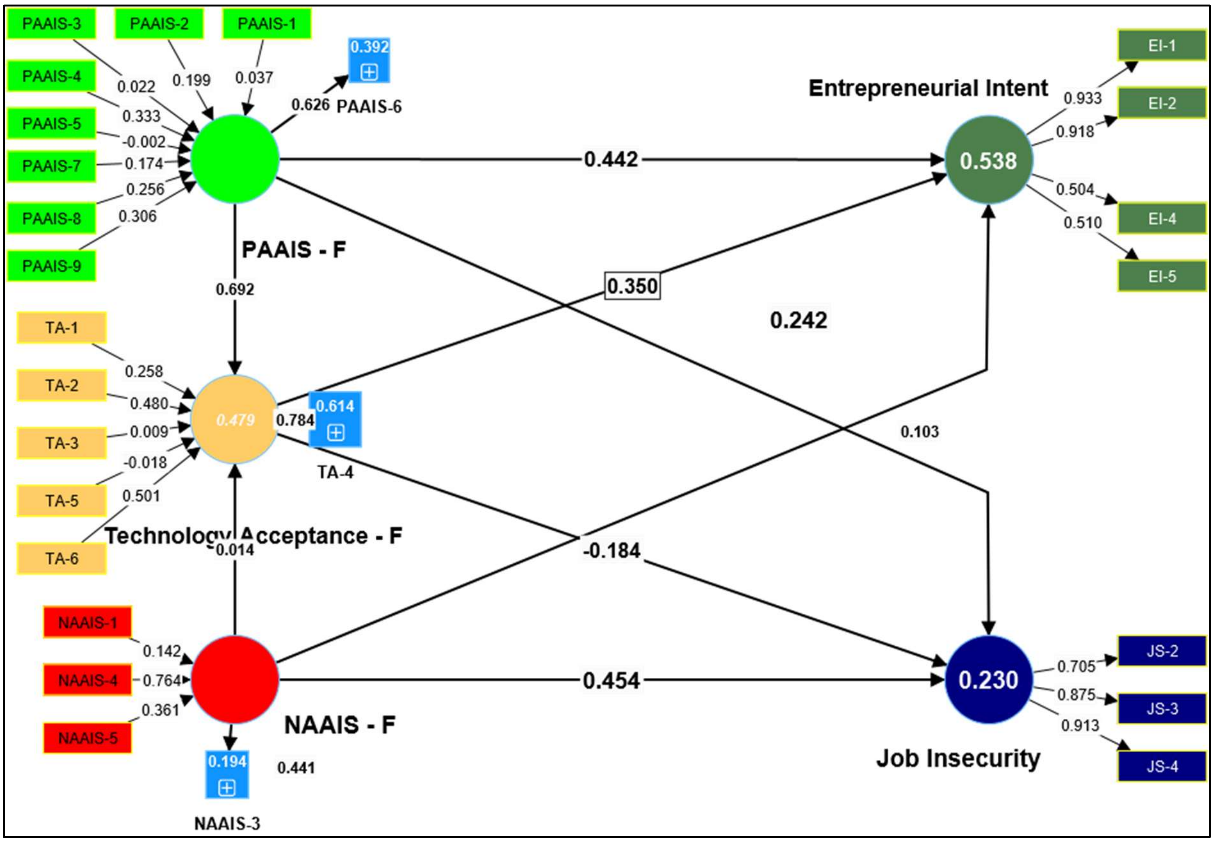


Table 1. Construct Reliability and Validity Test

Latent Variables	*Cronbach's alpha*	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*	*Average variance extracted (AVE)*
Entrepreneurial Intent	0.7700	0.9260	0.8230	0.5570
Job Insecurity	0.7770	0.7930	0.8730	0.6990

The analysis followed a comprehensive approach, meticulously validating the formative measurement models by assessing multicollinearity, path coefficients, outer weights, and outer loadings, while refining the reflective measurement models through systematic indicator removal until acceptable reliability and validity were established.

6.3 Structural Equation Model

Variance Inflation Factor (VIF) values were calculated for all indicators to identify potential multicollinearity issues. The analysis confirmed that the VIF values for most indicators were within acceptable limits, indicating no severe multicollinearity concerns. However, all the items for Entrepreneurial Intent (EI-1, EI-2, EI-4 and EI-5) & some Job Insecurity items (JS-3 and JS-4), exhibited relatively higher VIF values, suggesting potential multicollinearity.

Path Coefficient Analysis

The direct, indirect, and total effects of the paths in the structural model were evaluated, along with their respective p-values.

Table 2. Direct Effect

Direct Effect	*Original sample (O)*	*P values*
NAAIS - F -> Entrepreneurial Intent	0.1030	0.1570
NAAIS - F -> Job Insecurity	0.4540	0.0310
NAAIS - F -> Technology Acceptance - F	0.0140	0.7950
PAAIS - F -> Entrepreneurial Intent	0.4420	0.0000
PAAIS - F -> Job Insecurity	0.2420	0.0780
PAAIS - F -> Technology Acceptance - F	0.6920	0.0000
Technology Acceptance - F -> Entrepreneurial Intent	0.3500	0.0000
Technology Acceptance - F -> Job Insecurity	-0.1840	0.2140

*Different Colored Paths are significant

Table 3. Indirect Effect

Indirect Effect	*Original sample (O)*	*P values*
NAAIS - F -> Technology Acceptance - F -> Entrepreneurial Intent	0.0050	0.7960
NAAIS - F -> Technology Acceptance - F -> Job Insecurity	-0.0030	0.8260
PAAIS - F -> Technology Acceptance - F -> Entrepreneurial Intent	0.2420	0.0000

PAAIS - F -> Technology Acceptance - F -> Job Insecurity	-0.1280	0.2230

*Different Colored Paths are significant

Table 4. Total Effect

Total Effect	***Original sample (O)***	***P values***
NAAIS - F -> Entrepreneurial Intent	0.1080	0.1630
NAAIS - F -> Job Insecurity	0.4510	0.0310
NAAIS - F -> Technology Acceptance - F	0.0140	0.7950
PAAIS - F -> Entrepreneurial Intent	0.6840	0.0000
PAAIS - F -> Job Insecurity	0.1140	0.3720
PAAIS - F -> Technology Acceptance - F	0.6920	0.0000
Technology Acceptance - F -> Entrepreneurial Intent	0.3500	0.0000
Technology Acceptance - F -> Job Insecurity	-0.1840	0.2140

*Different Colored Paths are significant

Table 5. Mediation Effect

Relationship	***Direct Effect***	***Indirect Effect***	***Total Effect***	***VAF***	***Bias CI (L)***	***Bias CI (H)***
NAAIS - F -> Technology Acceptance – F -> Entrepreneurial Intent	0.0880	0.0050	0.0930	0.0538	-0.0290	0.0500
NAAIS - F -> Technology Acceptance – F -> Job Insecurity	0.4570	-0.0030	0.4540	-0.0066	-0.0350	0.0170
PAAIS - F -> Technology Acceptance – F -> Entrepreneurial Intent	0.4390	0.2450	0.6840	0.3582	0.1310	0.3810
PAAIS - F -> Technology Acceptance - F -> Job Insecurity	0.2420	-0.1320	0.1100	-	-0.3120	0.1480

*Different Colored Paths are significant

Insights:

a. NAAIS: Individuals with more negative attitudes toward AI tend to experience higher levels of Job Insecurity. This suggests that perceptions of AI as a threat to job security can influence individuals' overall sense of job stability and confidence.
b. PAAIS: Favorable attitudes towards AI (PAAIS) directly influence entrepreneurial intent (EI) and are partially mediated by technology acceptance (TA). The mediation analysis reveals a significant indirect pathway from PAAIS to EI through TA, with a VAF exceeding 30%, indicating the role of technology acceptance in fostering entrepreneurial aspirations.
c. Technology Acceptance: Greater acceptance of AI technologies directly fosters entrepreneurial intentions. This indicates that individuals who are more receptive to AI innovations are also more inclined to pursue entrepreneurial endeavors, potentially leveraging AI capabilities to drive business innovation and growth.

Coefficient of Determination

The analysis evaluated the R-square values, which represent the amount of variance explained in the endogenous latent variables.

Table 6. Coefficient of Determination

Latent Variable	*R-square*	*R-square adjusted*
Entrepreneurial Intent	0.5380	0.5290
Job Insecurity	0.2300	0.2150
Technology Acceptance - F	0.4790	0.4720

Insights:

a. The R-square values indicate the proportion of variance in each latent variable explained by the predictors included in the model.
b. Entrepreneurial Intent (EI) shows a relatively high R-square value, suggesting that the predictors in the model account for a significant portion of the variability in entrepreneurial aspirations.
c. Job Insecurity and Technology Acceptance - F have moderate R-square values, indicating that the predictors explain a moderate proportion of the variability in these constructs.

Effect Size

The f-square values were calculated to assess the effect size of each path on the endogenous latent variables.

Table 7. Effect Size

Path	*f-square*
NAAIS - F -> Entrepreneurial Intent	0.0230
NAAIS - F -> Job Insecurity	0.2670
NAAIS - F -> Technology Acceptance - F	0.0000
PAAIS - F -> Entrepreneurial Intent	0.2200
PAAIS - F -> Job Insecurity	0.0400
PAAIS - F -> Technology Acceptance - F	0.9190
Technology Acceptance - F -> Entrepreneurial Intent	0.1380
Technology Acceptance - F -> Job Insecurity	0.0230

Insights:

a. The F-square values indicate the proportion of variance in each endogenous variable explained by its predictors, taking into account the entire model.

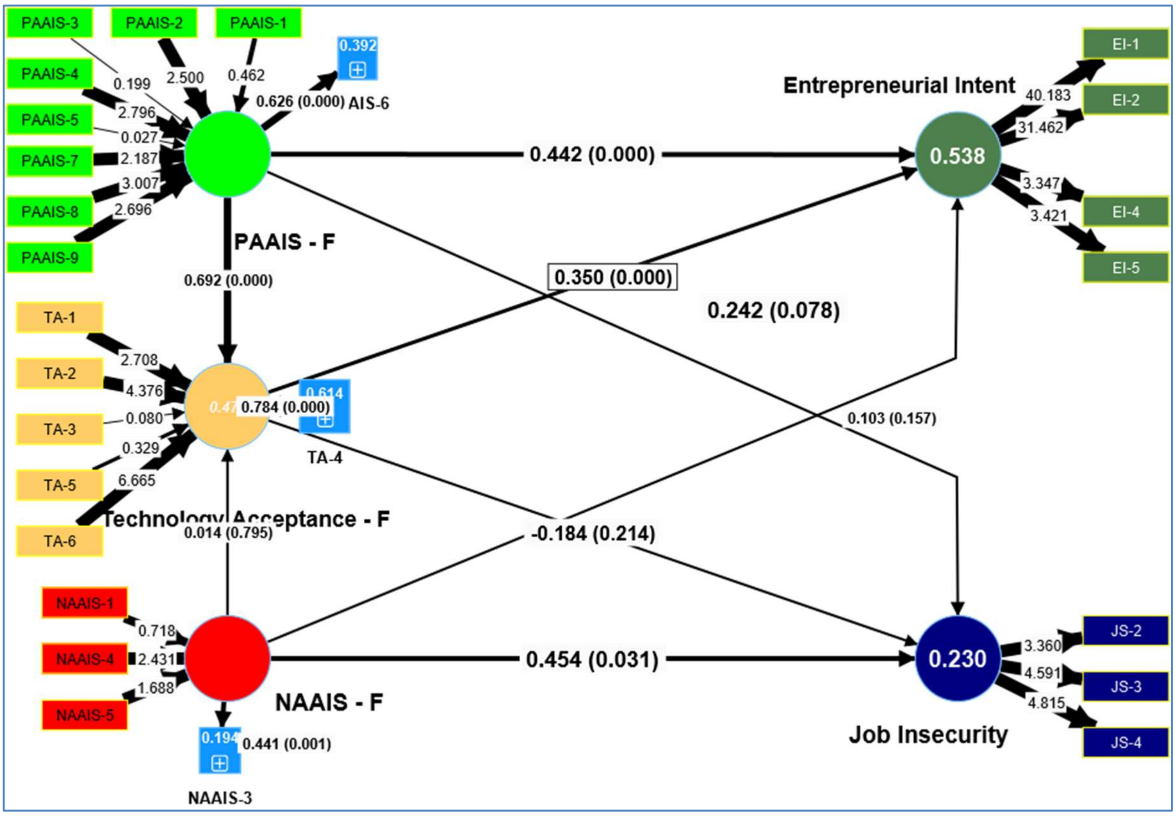
b. Negative attitudes towards AI (NAAIS - F) have a notable effect on job insecurity, indicating the perceived threat of AI-driven job displacement. However, they have a smaller effect on entrepreneurial intent and no significant effect on technology acceptance.

c. Positive attitudes towards AI (PAAIS - F) exert a considerable influence on both entrepreneurial intent and technology acceptance, underscoring the importance of favorable perceptions of AI in driving entrepreneurial aspirations and technology adoption.

d. Technology Acceptance - F demonstrates a moderate effect on entrepreneurial intent and a smaller effect on job insecurity, highlighting the role of individuals' willingness to adopt AI technologies in fostering entrepreneurial endeavors and alleviating concerns about job stability.

The following figure illustrates the final structural equation model, displaying path coefficients, p-values, and outer loadings of paths and items. It visually represents the relationships between latent variables and their corresponding observed indicators, providing insights into the strength and significance of these connections.

Figure 11. Final Model



Predictive Analysis

The analysis evaluated the predictive performance of the PLS-SEM model by examining the following measures:

i. Indicator-Level Prediction: The analysis assessed the predictive relevance of individual indicators using the Q^2 predict statistic and compared the root mean square error (RMSE) and mean absolute error (MAE) of the PLS-SEM model with those of the linear regression model (LM).
   a. Significant Indicators (Q^2 predict > 0): EI-1, EI-2, JS-2, JS-3, JS-4, NAAIS-3, PAAIS-6, TA-4, TA-1, TA-2, TA-3, TA-6
   b. Insignificant Indicators (Q^2 predict ≤ 0): EI-4, EI-5, TA-5

For most indicators with significant Q^2 predict values, the PLS-SEM model exhibited lower RMSE and MAE values compared to the LM model, suggesting better predictive performance.

Table 8. Item Prediction

Items	*Q²predict*	*PLS-SEM_RMSE*	*PLS-SEM_MAE*	*LM_RMSE*	*LM_MAE*
EI-1	0.486	0.772	0.602	0.771	0.588
EI-2	0.387	0.806	0.642	0.794	0.628
EI-4	-0.044	1.217	0.942	1.22	0.99
EI-5	-0.055	1.223	1.005	1.165	0.977
JS-2	0.078	1.102	0.925	1.061	0.861
JS-3	0.075	1.224	1.006	1.169	0.929
JS-4	0.158	1.092	0.908	0.994	0.787
NAAIS-3	0.166	0.95	0.764	0.825	0.638
PAAIS-6	0.343	0.647	0.48	0.616	0.468
TA-4	0.321	0.851	0.666	0.853	0.678
TA-1	0.182	0.949	0.754	0.971	0.764
TA-2	0.252	0.944	0.771	0.959	0.773
TA-3	0.167	1.011	0.835	0.994	0.802
TA-5	0.015	0.911	0.74	0.905	0.702
TA-6	0.351	1.049	0.854	1.067	0.861

ii. Latent Variable-Level Prediction: The analysis evaluated the predictive relevance of the latent variables using the Q^2 predict statistic and compared the RMSE and MAE of the PLS-SEM model with those of the LM model.
   a. Significant Latent Variables (Q^2 predict > 0): Entrepreneurial Intent (Q^2 predict = 0.416) Technology Acceptance-F (Q^2 predict = 0.416)
   b. Insignificant Latent Variable (Q^2 predict ≤ 0): Job Insecurity (Q^2 predict = 0.150)

For the significant latent variables, Entrepreneurial Intent and Technology Acceptance-F, the PLS-SEM model exhibited lower RMSE and MAE values compared to the LM model, indicating better predictive performance.

Table 9. Latent Variable Prediction

Latent Variable	***Q²predict***	***RMSE***	***MAE***
Entrepreneurial Intent	0.416	0.767	0.579
Job Insecurity	0.15	0.933	0.765
Technology Acceptance - F	0.416	0.772	0.633

The PLS-SEM model demonstrated superior predictive performance compared to the LM model for most indicators and the latent variables Entrepreneurial Intent and Technology Acceptance-F. Still, the model's predictive performance was not significant for the Job Insecurity latent variable and a few indicators, such as EI-4, EI-5, and TA-5.

7. Conclusion

7.1 Conclusion

This comprehensive study provides valuable insights into the complex relationships between individuals' perceptions of artificial intelligence, their job market experiences, and entrepreneurial intentions. The exploratory data analysis revealed several noteworthy patterns, including the negative correlation between work experience and both job insecurity and entrepreneurial intent, as observed in the works of Golin and Rauh (2022) and Presbitero and Teng-Calleja (2023), as well as the non-linear relationship between income levels and entrepreneurial aspirations, aligning with the findings of Hou et al. (2019) and Valliere (2015).

The structural equation modeling (SEM) analysis further substantiates these findings, demonstrating that negative attitudes towards AI (NAAIS) directly influence job insecurity, while positive attitudes (PAAIS) foster entrepreneurial intent, partially mediated by technology acceptance. This underscores the critical role of AI perceptions in shaping both job-related anxieties and entrepreneurial motivation, as suggested by the literature on the implementation of AI for business model innovation (Reim et al., 2020; Thommie Burström et al., 2021) and the integration of AI into manufacturing business models (Thommie Burström et al., 2021).

The predictive analysis indicates that the PLS-SEM model outperforms linear regression in forecasting entrepreneurial intent and technology acceptance, reinforcing the appropriateness of the proposed framework in capturing these intricate relationships, as advocated by the methodological guidance provided by Regmi et al. (2016), Dash and Paul (2021), Hair et al. (2017, 2011), and Ramli et al. (2018). However, the model's predictive power is less pronounced for job insecurity, suggesting the need for further refinement in this domain, as highlighted by the literature on the psychological ramifications of AI-induced job displacement fears (Golin and Rauh, 2022; Presbitero and Teng-Calleja, 2023).

In conclusion, the study provides a comprehensive understanding of the interplay between AI attitudes, job market dynamics, and entrepreneurial endeavors. These findings offer valuable insights for researchers, policymakers, and industry practitioners as they navigate the evolving technological landscape and its societal implications, as advocated by the literature on the role of AI and machine learning in job automation (Peng & Bhaskar, 2023). By elucidating the complex interrelationships between these key constructs, this research lays the foundation for more nuanced investigations and strategic interventions aimed at fostering a thriving, AI-empowered workforce and entrepreneurial ecosystem.

7.2 Managerial Implications and Opportunities

The insights gleaned from this comprehensive study hold important implications for managers and industry practitioners navigating the evolving technological landscape. The research findings underscore the pivotal role of individuals' perceptions and attitudes towards AI in shaping both their job market experiences and entrepreneurial endeavors.

One key implication is the need for organizations to proactively address negative perceptions of AI among their workforce. As the study reveals, negative attitudes towards AI (NAAIS) directly contribute to heightened job insecurity. To mitigate these concerns, managers should consider implementing targeted training and communication programs that educate employees on the capabilities and limitations of AI technologies, as suggested by the work of Reim et al. (2020) on leveraging AI for business model innovation. By fostering a better understanding of AI, organizations can help alleviate unfounded fears and anxieties, thereby promoting a more resilient and adaptable workforce.

Conversely, the research findings indicate that positive attitudes towards AI (PAAIS) can have a significant impact on cultivating entrepreneurial intent, partially mediated by technology acceptance. This presents a valuable opportunity for organizations to leverage their employees' AI-positive mindsets to drive innovation and business growth. Managers could explore strategies to encourage intrapreneurship, such as providing AI-focused training and resources, as well as creating dedicated incubation programs, drawing inspiration from the guidance offered by Thommie Burström et al. (2021) on integrating AI into business models.

Furthermore, the study's insights into the non-linear relationship between income levels and entrepreneurial intent suggest that managers should consider tailoring their support and incentive structures to cater to the varied entrepreneurial aspirations across different income segments. This nuanced understanding can help organizations better nurture their employees' innovative potential, in alignment with the recommendations from Hou et al. (2019) and Valliere (2015) on the factors shaping entrepreneurial intention.

By proactively addressing AI perceptions, fostering a culture of AI-driven innovation, and aligning support structures with the diverse entrepreneurial motivations of their workforce, managers can position their organizations to thrive in the AI-powered business landscape of the future. These strategic interventions, underpinned by the research findings and the broader literature, can unlock new avenues for sustainable growth and competitiveness.

7.3 Regulatory Implications

The insights gleaned from this study hold significant implications for policymakers and regulatory bodies as they navigate the complex landscape of AI-driven technological advancements and their societal impact.

One key implication is the need for a balanced regulatory approach that addresses both the opportunities and challenges presented by AI adoption. The research findings underscore the double-edged nature of AI perceptions, where negative attitudes (NAAIS) contribute to heightened job insecurity, while positive attitudes (PAAIS) foster entrepreneurial intent and technology acceptance. This suggests that policymakers should strive to cultivate a regulatory environment that mitigates the potential for AI-induced job displacement, while simultaneously nurturing the innovative potential of AI-empowered entrepreneurship.

Addressing the fears and anxieties surrounding AI-driven automation should be a priority for policymakers. Drawing on the insights from the literature on the psychological ramifications of job insecurity and displacement (Golin and Rauh, 2022; Presbitero and Teng-Calleja, 2023), regulatory bodies could explore the implementation of transitional support mechanisms, such as skills-based retraining programs and income assistance, to help workers adapt to the changing labor market dynamics. By proactively addressing the negative perceptions of AI, policymakers can help alleviate the psychological burden on workers and foster a more resilient and adaptable workforce.

At the same time, the research findings highlight the potential of positive AI perceptions in driving entrepreneurial intent and technology adoption. Policymakers should consider enacting regulations and incentive structures that encourage the development and deployment of AI technologies, while ensuring appropriate safeguards are in place. This could include targeted tax credits, research and development funding, and regulatory sandboxes that enable the responsible experimentation and scaling of AI-powered business models, as suggested by the literature on the implementation of AI for business model innovation (Reim et al., 2020; Thommie Burström et al., 2021).

Additionally, the study's insights into the nuanced relationship between income levels and entrepreneurial intent underscore the need for a multifaceted regulatory approach. Policymakers should explore policies that foster entrepreneurship across diverse income segments, drawing on the guidance provided by Hou et al. (2019) and Valliere (2015) on the factors shaping entrepreneurial intention. This could involve accessible financing schemes, mentorship programs, and regulatory frameworks that enable the growth of AI-powered startups and small-to-medium enterprises.

By adopting a balanced and comprehensive regulatory approach, policymakers can harness the transformative potential of AI while mitigating its potential negative societal impacts. This holistic strategy, informed by the research findings and the broader literature, can help cultivate a thriving, AI-empowered ecosystem that fosters innovation, job resilience, and sustainable economic growth.

7.4 Limitations and Future Research

While this study provides valuable insights into the complex relationships between AI perceptions, job market experiences, and entrepreneurial intentions, it is not without limitations, which present opportunities for future research.

One key limitation is the cross-sectional nature of the data, which restricts the ability to establish causal relationships and examine the dynamic evolution of the constructs over time. Future longitudinal studies would be valuable in elucidating the long-term implications of AI perceptions and their influence on job market outcomes and entrepreneurial pursuits. As suggested by the literature on technology acceptance and job automation (Marangunić & Granić, 2015; Peng & Bhaskar, 2023), tracking these variables over an extended period could provide deeper insights into the temporal interplay between these factors.

Additionally, the study's focus on a specific geographical context and population limits the generalizability of the findings. Conducting cross-cultural and cross-national comparisons, as exemplified in the works of Kelley et al. (2021) and Nomura et al. (2006), would be instrumental in uncovering the influence of socio-cultural factors on the relationships explored in this research. This would further enhance the understanding of the nuanced interplay between AI attitudes, job market dynamics, and entrepreneurial endeavors in diverse global settings.

Another limitation is the reliance on self-reported data, which can be susceptible to various biases. Future studies could explore the incorporation of objective measures, such as behavioral data and performance indicators, to triangulate the findings and gain a more comprehensive understanding of the phenomena. This aligns with the methodological guidance provided by Regmi et al. (2016) and Willaby et al. (2015) on the effective application of online surveys and partial least squares structural equation modeling (PLS-SEM) in research.

Furthermore, the study's focus on the overarching constructs of positive and negative attitudes towards AI (PAAIS and NAAIS) presents an opportunity for more granular investigations. Future research could delve into the specific dimensions and sub-components of AI perceptions, drawing inspiration from the multidimensional scales developed by Kieslich et al. (2020) and Nomura et al. (2006) for measuring threat perceptions associated with AI and robots. This could provide a more nuanced understanding of the differential impacts of various AI-related attitudes on job market experiences and entrepreneurial intentions.

Finally, the model's limited predictive power for job insecurity suggests the need for further refinement and the inclusion of additional variables to enhance the explanatory capacity in this domain. Incorporating constructs from the broader literature on job insecurity and its antecedents, such as organizational support, job characteristics, and individual factors (Srivastava, 1977; Presbitero and Teng-Calleja, 2023), could lead to a more comprehensive model that better captures the complexity of job-related anxieties in the face of technological advancements.

By addressing these limitations and exploring the future research directions outlined, scholars can build upon the foundations laid by this study, further advancing the understanding of the intricate interplay between AI perceptions, job market dynamics, and entrepreneurial endeavors. These insights will be instrumental in informing evidence-based policymaking and guiding organizational strategies as they navigate the evolving technological landscape.

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APPENDIX 1

Survey Design

Table 1 – Questionnaire Items

Survey Item	Construct Code	Remarks
Age	Demographics	
Gender	Demographics	
Highest Education	Demographics	
Occupation	Demographics	
Years of Work Experience (in Years)	Demographics	
If worked in a start-up or have start-up experience	Demographics	
Your Last Income Level (p.a.)	Demographics	
For routine transactions, I would rather interact with an AI system than with a human.	PAAIS-1	
Organisations use AI unethically.	NAAIS-1	
I think artificially intelligent systems make many errors.	NAAIS-2	
I am interested in using AI systems in my daily life.	PAAIS-2	
I think AI is dangerous.	NAAIS-3 (GI)	Global Item (Formative)
AI can have positive impacts on people's wellbeing.	PAAIS-3	
AI is exciting.	PAAIS-4	
An AI agent would be better than an employee in many routine jobs.	PAAIS-5	
There are many beneficial applications of AI.	PAAIS-6 (GI)	Global Item (Formative)
Artificially intelligent systems can perform better than humans.	PAAIS-7	
Much of society will benefit from a future full of AI	PAAIS-8	
I would like to use AI in my own job.	PAAIS-9	
People like me will suffer if AI is used more and more.	NAAIS-4	
AI is used to spy on people	NAAIS-5	
With the help of AI, I'll experiment to solve customer problems through my business idea.	EI-1	
I think AI and machine learning remove a lot of barriers for launching new startups for me.	EI-2	
I feel like AI's growth makes starting a business seem hard for people with skills like mine.	EI-3 (reverse encoded)	Reverse Coded

My professional goal is to become an entrepreneur.	EI-4	
I am determined to create a firm in the future.	EI-5	
How will an advancement in AI affect future entrepreneurship opportunities and obstacles for startups in your specialty area? (OPTIONAL)	Open Ended	
I don't think automation and AI will greatly change the job market.	JS-1	
I'm not sure about my job or future because of AI and automation.	JS-2	
I would be grateful if you could select agree. Attention Checks	Attention Check	
I'm concerned that the skills I have now might no longer be useful because of AI.	JS-3	
I worry that using AI programs more will make jobs like mine less important.	JS-4	
What are the biggest potential negative / positive impacts of AI on jobs and careers in your field in the next decade? (OPTIONAL)	Open Ended	
I'm unsure about switching to AI-powered tools.	TA-1	
I actively adopt technologies like machine learning and automation programs.	TA-2	
I keep upgrading my skills in AI-related areas like data science and intelligent systems.	TA-3	
I use new tools, apps and platforms enabled by AI algorithms.	TA-4	
I make sure to check if the AI tools are good and safe before using them.	TA-5	
I use AI powered tools...	TA-6	
What do you look for in an AI system before adopting it? (OPTIONAL)	Open Ended	
Feedback - (Open Ended Question)	Open Ended	

Scoring for Scales

1. Entrepreneurial Intentions Scale:

- 5-point Likert scale from "Strongly Disagree" to "Strongly Agree"
- Take the mean of all items to calculate the overall entrepreneurial intentions score
- A higher mean indicates greater entrepreneurial intentions

2. Job Insecurity Scale:

- 5-point Likert scale from "Strongly Disagree" to "Strongly Agree"
- Take the mean of all items except reverse-coded ones
- A higher mean indicates greater job insecurity
- For reverse-coded items, reverse the scores before taking the mean

3. Technology Adoption Scale:

- 5-point Likert scale from "Strongly Disagree" to "Strongly Agree"
- Take the mean of all items except reverse-coded one
- A higher mean indicates greater technology adoption tendencies
- Reverse code is the hesitance to adopt an item before taking the mean

Scoring for GAAIS:

Response Options	Positive	Negative
Strongly Disagree	1	5
Disagree	2	4
Neutral	3	3
Agree	4	2
Strongly Agree	5	1

Then we would take the mean of the "Positive Items" to form an **Overall Score** for a positive subscale, similarly for a negative subscale. The higher the score on each subscale, the more positive the attitude.

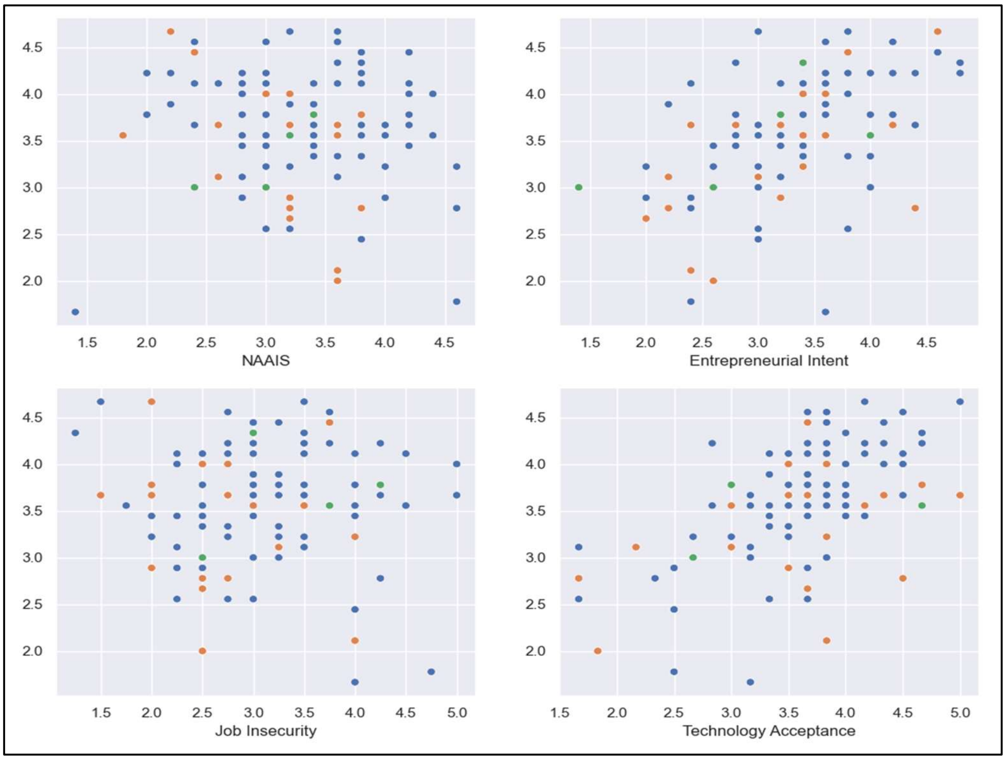
This will result in two different scales: **Positive GAAIS** and **Negative GAAIS,** which will provide insights into their positive and negative attitudes toward AI.

APPENDIX 2

Scale Scatterplot Matrix

1. This matrix of scatter plots shows the relationships between the PAAIS scale and other scales (NAAIS, Job Insecurity, Entrepreneurial Intent, Technology Adoption)

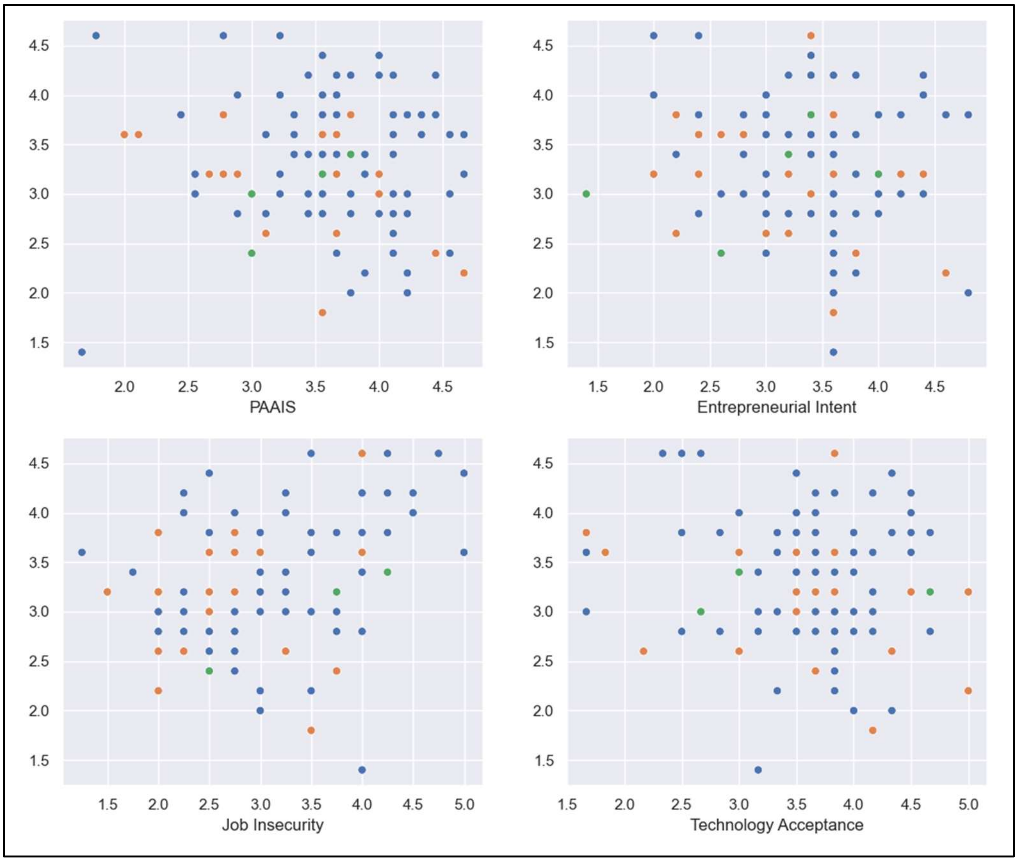
Figure 1 PAAIS Scatter Plot Matrix



The scatter plot matrix reveals a positive correlation between Positive Attitudes Toward AI (PAAIS) and both Entrepreneurial Intent (EI) and Technology Acceptance (TA), while exhibiting a negative correlation with Negative Attitudes Toward AI (NAAIS) and Job Insecurity. These associations underscore the influence of AI perceptions on entrepreneurial aspirations and technological adoption across varied employment statuses.

2. This matrix of scatter plots illustrates the relationships between the NAAIS (Negative Attitudes Toward AI Scale) and other scales (PAAIS, Entrepreneurial Intent, Job Insecurity, Technology Adoption).

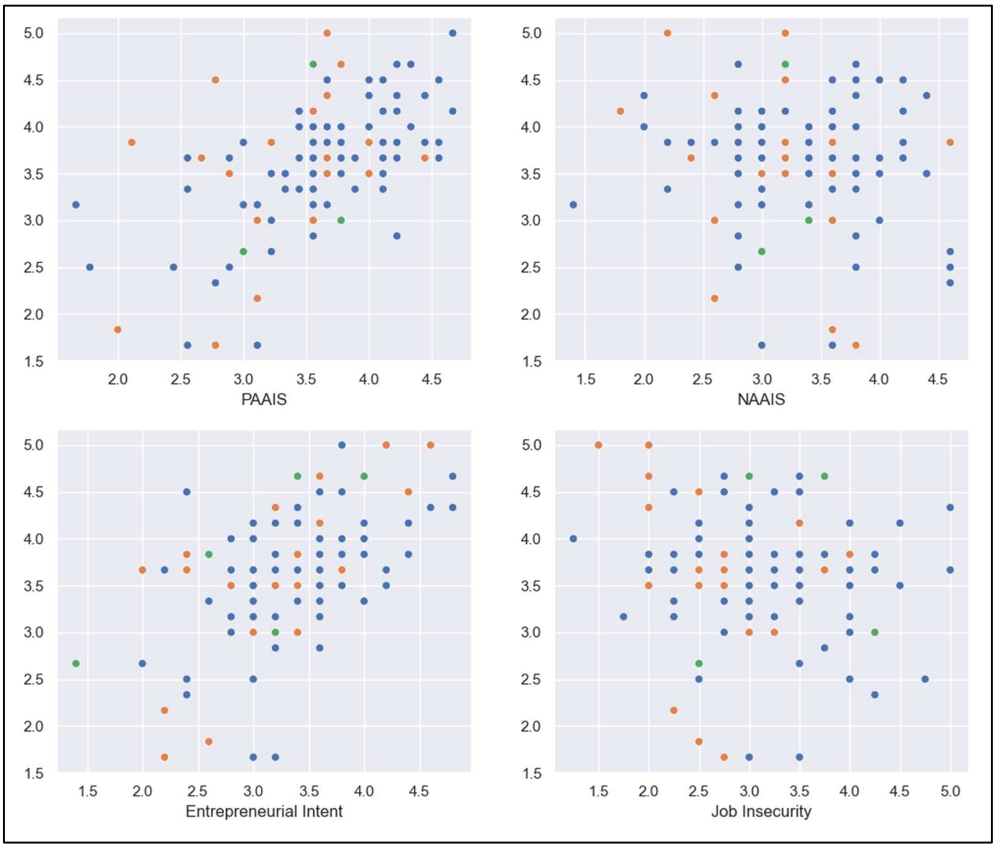
Figure 2. NAAIS



Negative Attitudes Toward AI (NAAIS) exhibit a negative correlation with Positive Attitudes Toward AI (PAAIS), a moderately pronounced negative correlation with Entrepreneurial Intent (EI), and a positive correlation with Job Insecurity (JS), indicating its role in shaping both AI perceptions and job security concerns.

3. This matrix of scatter plots shows the relationships between the Technology Adoption and other scales (PAAIS, NAAIS, Entrepreneurial Intent, Job Insecurity).

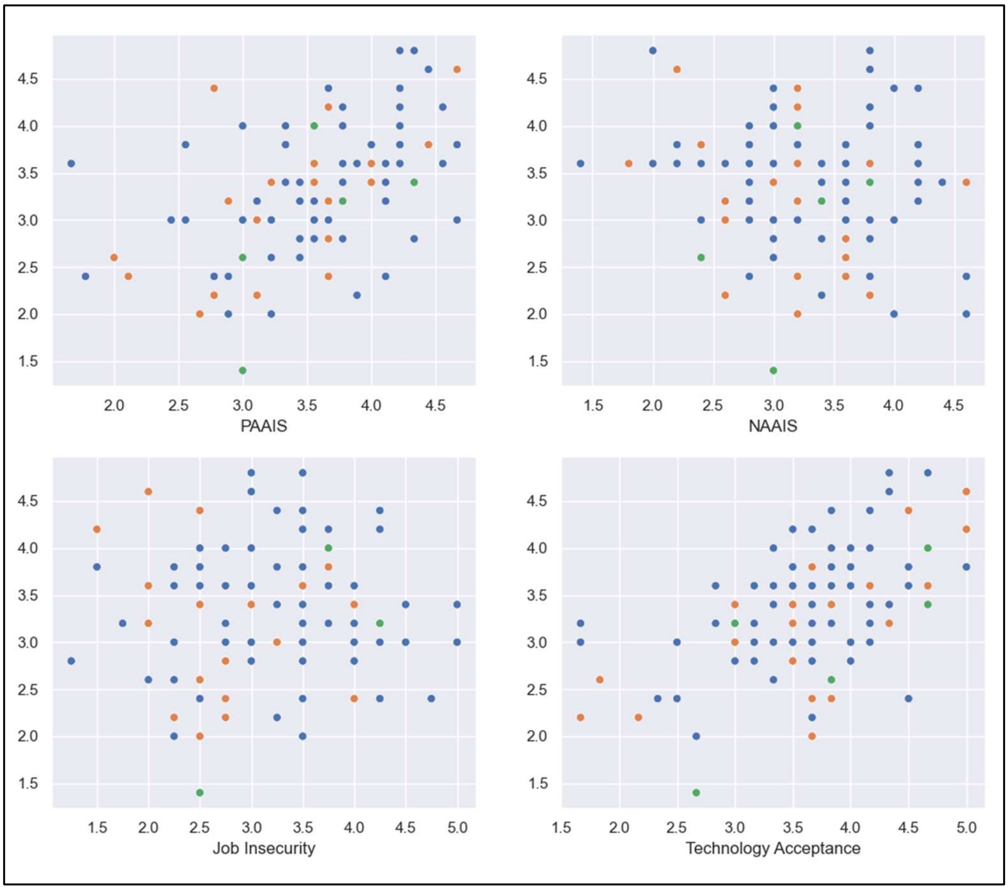
Figure 3 Technology Adoption



Technology Acceptance (TA) shows positive correlations with PAAIS and EI, with a particularly strong relationship with itself (TA). Additionally, it maintains a negative correlation with NAAIS and JS, highlighting its pivotal role in fostering positive AI perceptions and entrepreneurial intentions while mitigating negative attitudes and job insecurity concerns.

4. This matrix of scatter plots illustrates the relationships between the Entrepreneurial Intent scale and other scales (PAAIS, NAAIS, Job Insecurity, Technology Adoption).

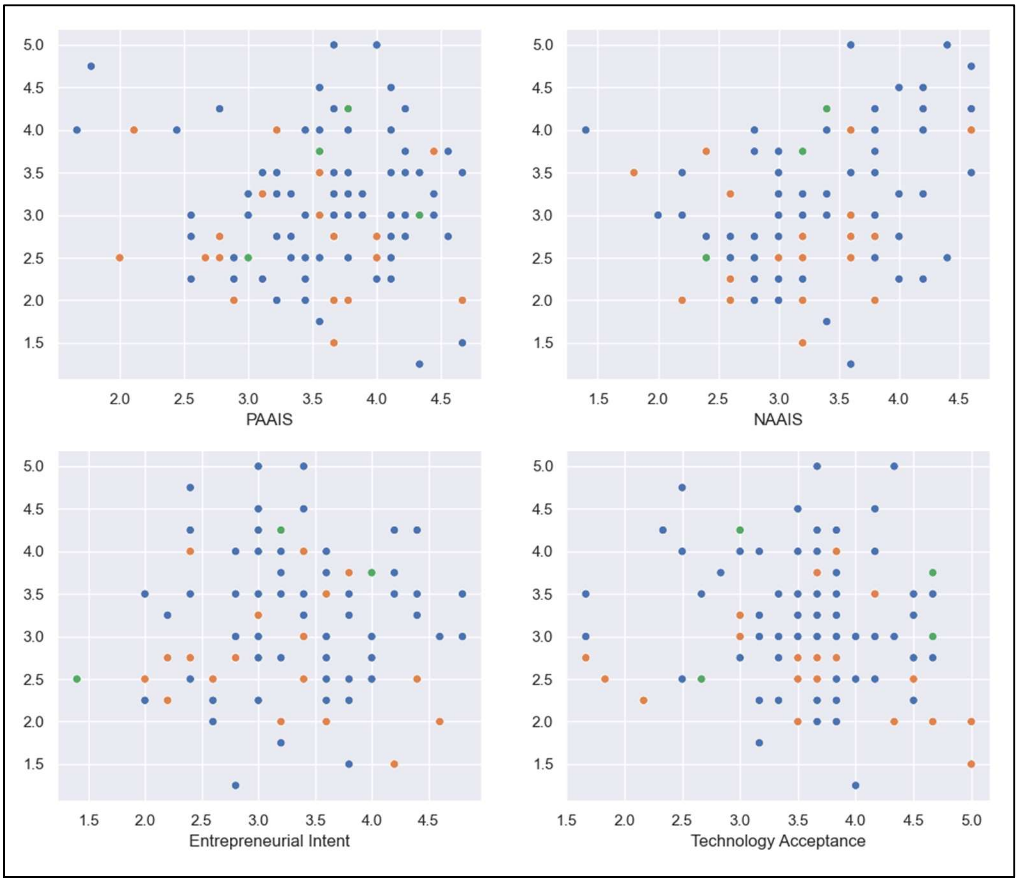
Figure 4 Entrepreneurial Intent



Entrepreneurial Intent (EI) demonstrates positive correlations with PAAIS and TA, indicating the influence of positive AI perceptions and technological acceptance on entrepreneurial aspirations. It also exhibits a negative correlation with NAAIS, suggesting that negative attitudes toward AI may hinder entrepreneurial intentions, while its relationship with JS appears indistinct.

5. This matrix of scatter plots shows the relationships between the Job Insecurity and other scales (PAAIS, NAAIS, Entrepreneurial Intent, Technology Adoption).

Figure 5 Job Insecurity



Job Insecurity (JS) displays relationships as described previously, showcasing its positive correlation with NAAIS and its negative correlation with PAAIS and TA. This suggests that perceptions of job insecurity may be influenced by negative attitudes toward AI, while positive AI perceptions and technological acceptance may alleviate such concerns.

Reflective Model Testing

Figure 6. Reflective Model (Before Deletion)

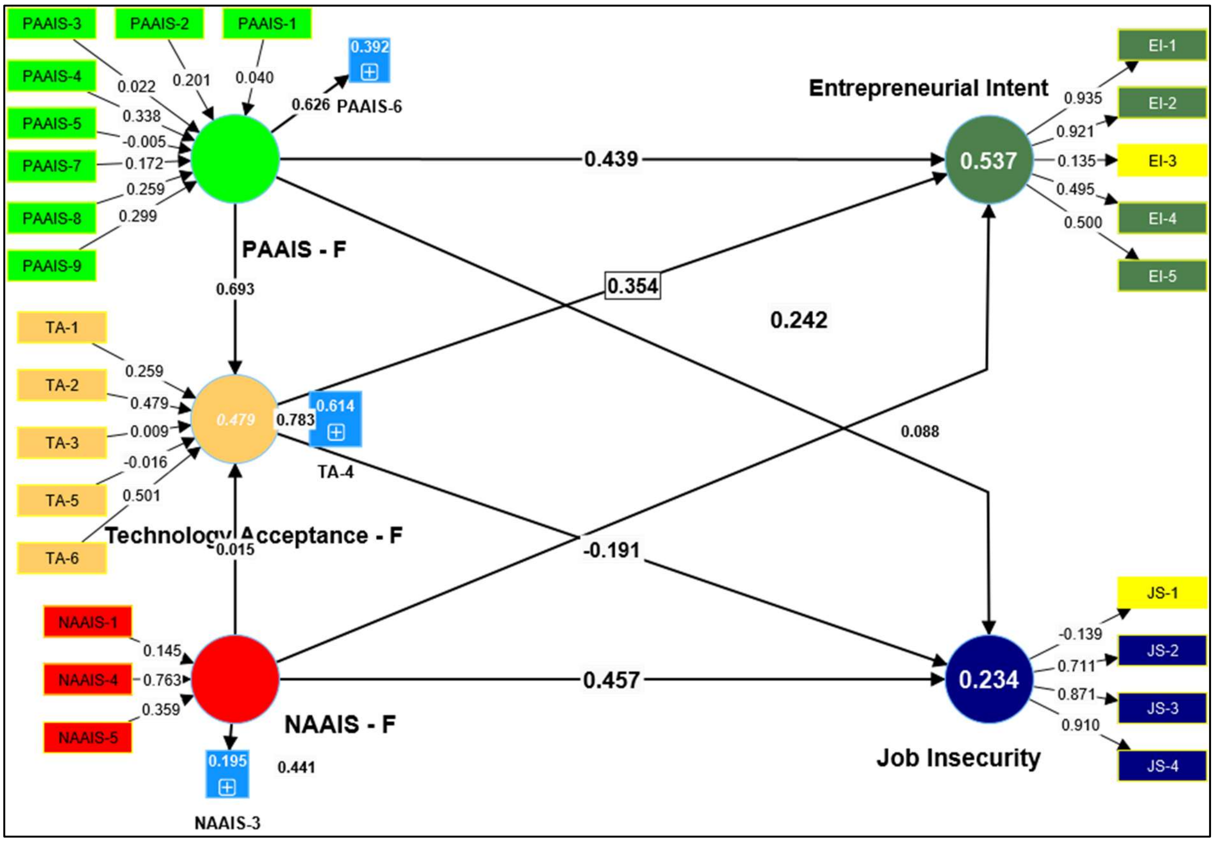


Table 2 – Reliability and Validity Test

Latent Variables	*Cronbach's alpha*	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*	*Average variance extracted (AVE)*
Entrepreneurial Intent	*0.6530*	*0.9260*	*0.7630*	*0.4470*
Job Insecurity	*0.5000*	*0.7820*	*0.7460*	*0.5280*

Reflective Entrepreneurial Intent (EI) Scale:

a. Initially, the EI scale exhibited low outer loadings with insignificant values.
b. Indicators with lower outer loadings were systematically removed until acceptable reliability and validity measures were achieved.
c. These measures included Cronbach's alpha, composite reliability (rho_a and rho_c), and Average Variance Extracted (AVE), evaluated against recommended thresholds.

Reflective Job Insecurity (JS) Scale:

a. The JS scale underwent a similar process of iterative indicator removal due to low and insignificant outer loadings.
b. Indicators were eliminated until the reliability and validity measures (Cronbach's alpha, composite reliability, and AVE) reached satisfactory levels.

Final Model VIF

Table 3 – Variance Inflated Factor

Items	EI-1	EI-2	EI-4	EI-5	JS-2	JS-3	JS-4
VIF	3.599	3.561	3.422	3.416	1.22	3.064	3.233
Items	PAAIS-1	PAAIS-2	PAAIS-3	PAAIS-4	PAAIS-5	PAAIS-6	PAAIS-7
VIF	1.155	1.664	1.592	2.169	1.464	1	1.455
Items	PAAIS-8	PAAIS-9	NAAIS-1	NAAIS-3	NAAIS-4	NAAIS-5	
VIF	1.765	2.448	1.176	1	1.154	1.19	
Items	TA-1	TA-2	TA-3	TA-4	TA-5	TA-6	
VIF	1.268	2.339	2.626	1	1.196	1.656	