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BEYOND TECHNOLOGY ADOPTION: THE ROLE OF AI INTEGRATION QUALITY IN SHAPING STUDENT SATISFACTION AND CAREER CONFIDENCE

Sena ÖZCAN KALFA[1]

[1]Ministry of National Education, Denizli, Türkiye

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Corresponding Author:
Sena Özcan Kalfa

ABSTRACT

This study investigates the effects of perceived technology usefulness and perceived artificial intelligence (AI) integration quality on student satisfaction, continuance intention, and career confidence in higher education. The research model is developed based on the Technology Acceptance Model (TAM), with AI integration quality—conceptualized through accuracy, transparency, and ethical perception—introduced as a first-order reflective construct. Data were collected from undergraduate students in Türkiye (n = 236) and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that perceived technology usefulness strongly influences perceived AI integration quality ($\beta = 0.733$), which in turn enhances student satisfaction ($\beta = 0.385$) and has a smaller direct effect on career confidence ($\beta = 0.111$). Student satisfaction substantially predicts continuance intention ($\beta = 0.688$) and career confidence ($\beta = 0.322$), while continuance intention also contributes to career confidence ($\beta = 0.421$). The results support an indirect pathway in which technology-related perceptions contribute to career confidence mainly through satisfaction and persistence-related mechanisms.

1. INTRODUCTION

Higher education institutions are increasingly compelled to incorporate advanced digital technologies and artificial intelligence (AI) applications into teaching and learning environments as part of the ongoing process of digital transformation. Tools such as learning management systems, adaptive learning technologies, and AI-driven feedback mechanisms are not only enhancing students' learning experiences but also redefining conventional pedagogical practices. These developments generate a range of outcomes that go beyond academic achievement, influencing students' satisfaction, their commitment to educational programs, and their confidence regarding future careers. Accordingly, understanding how technological integration shapes educational outcomes has become a critical issue from both theoretical and empirical perspectives.

Within the field of information systems, the Technology Acceptance Model (TAM) continues to serve as one of the most influential frameworks for explaining technology usage behavior.

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In this context, perceived usefulness refers to an individual's evaluation of the extent to which a technological system contributes to improved performance and is considered a key predictor of behavioral intention (Davis, 1989). Previous research has consistently shown that when students perceive digital tools as beneficial, they tend to demonstrate higher levels of engagement, motivation, and academic success. Thus, perceived usefulness should be conceptualized not merely as a determinant of usage intention, but also as a broader factor shaping overall student experience.

Artificial intelligence technologies provide substantial opportunities in educational settings, including the delivery of personalized learning experiences, automated evaluation processes, and instant feedback. Nevertheless, alongside these advantages, increasing attention has been directed toward potential concerns related to accuracy, transparency, and ethical considerations. International organizations emphasize that the effective use of AI in education requires adherence to principles such as fairness, accountability, and human oversight (UNESCO, 2021), while also highlighting the importance of trust-oriented AI systems in digital learning environments (OECD, 2023). In this respect, students' evaluations of AI integration quality—particularly regarding reliability, ethical alignment, and transparency—are likely to play a crucial role in shaping psychological outcomes such as satisfaction and confidence.

Student satisfaction is widely acknowledged as a central factor influencing persistence in higher education. Students who report higher satisfaction levels are generally more engaged and more likely to continue and complete their academic programs. Evidence from learning analytics research further indicates that active participation in digital learning environments is associated with lower dropout rates (de Oliveira et al., 2021). These findings imply that technological factors may affect student retention indirectly through experiential and psychological pathways rather than through direct mechanisms alone.

Despite the expanding literature, prior studies have predominantly focused on technology acceptance in relation to behavioral intention or performance-related outcomes. Comparatively less attention has been given to integrating broader psychosocial constructs—such as satisfaction, continuance intention, and career confidence—within a unified analytical framework. In particular, the influence of AI integration quality, including its ethical and transparency dimensions, on students' career confidence remains insufficiently examined. However, students' experiences within digitally enriched learning environments may significantly shape their perceptions of professional competence and future career prospects.

Career confidence is a complex construct that involves not only expectations regarding employment after graduation but also perceptions of competence, self-efficacy, and control over future career trajectories (Lent et al., 1994). Higher education plays a crucial role in developing both academic knowledge and professional identity, thereby influencing individuals' readiness for the labor market (Yorke, 2006; Tomlinson, 2017). From this perspective, analyzing the role of digital learning environments and AI integration in shaping career confidence is essential for understanding the broader implications of technological transformation in education (Selwyn, 2016; Holmes et al., 2019).

Building on this background, the present study conceptualizes career confidence as a key outcome variable in the higher education context. It investigates the relationships between perceived technology usefulness, AI integration quality, student satisfaction, and career confidence within an integrated structural framework. By combining insights from technology acceptance, student retention, and career development literatures, the study aims to offer both theoretical advancement and empirical evidence based on the Turkish higher education setting. More specifically, the study addresses the following research question: How do perceived technology usefulness and perceived AI integration quality jointly shape student satisfaction, continuance intention, and career confidence in higher education? The central research problem is that existing technology-adoption studies explain whether students accept digital tools, but less often explain how the perceived quality of AI integration translates into broader academic and career-related outcomes. The study therefore contributes by extending TAM with AI integration quality and career confidence, thereby linking technology acceptance, student experience, retention-related intention, and career development in a single PLS-SEM framework.

2. HYPOTHESES AND MODEL DEVELOPMENT

The proposed research framework seeks to examine how students' perceptions of technology and artificial intelligence contribute to both direct and indirect outcomes, particularly student satisfaction and career confidence, within the higher education context.

2.1.Theoretical and Conceptual Framework

The conceptual logic of the study is grounded in the Technology Acceptance Model (TAM), information systems success perspectives, student retention literature, and social cognitive career theory. TAM suggests that perceived usefulness shapes users' evaluations and intentions toward technology (Davis, 1989; Venkatesh & Davis, 2000). However, AI-enabled educational systems are not evaluated only in terms of usefulness; students also consider whether AI outputs are accurate, transparent, fair, and ethically appropriate (Holmes et al., 2019; UNESCO, 2021; OECD, 2023). For this reason, AI integration quality is positioned as an extended quality-related construct that captures students' evaluation of how responsibly and pedagogically AI is embedded in their learning environment.

The model further assumes that technology-related perceptions influence student outcomes through experiential and motivational pathways. Student satisfaction reflects students' overall evaluation of their academic experience and is closely connected to persistence in higher education (Tinto, 1993; Thomas, 2012). Career confidence, in turn, is informed by social cognitive career theory, which emphasizes self-efficacy, learning experiences, and outcome expectations as foundations of career development (Lent et al., 1994). Thus, the present framework treats perceived technology usefulness and AI integration quality as antecedents, student satisfaction and continuance intention as intervening pathway variables, and career confidence as a distal educational outcome.

2.2. Perceived Technology Usefulness and AI Integration Quality

Perceived technology usefulness reflects students’ subjective evaluations of how effectively technological tools support their academic performance. Beyond its well-established role in predicting behavioral intention, perceived usefulness may also influence how individuals assess the overall quality of technological systems. When students perceive a technology as beneficial, they are more likely to view it as reliable, accurate, and well-integrated into their learning environment.

In this regard, perceived AI integration quality is specified as a standard first-order reflective latent construct, not as a higher-order construct. Accuracy, transparency, and ethical appropriateness define the common conceptual domain that gives rise to students’ overall quality evaluations; they are therefore treated as related manifestations of the same underlying perception rather than as separate dimensions combined formatively. The three indicators are expected to covary and to be interchangeable manifestations of the latent perception. This reflective specification is consistent with the study’s aim of capturing students’ overall evaluation of responsible and pedagogically appropriate AI integration.

H1: Perceived technology usefulness has a positive effect on perceived AI integration quality.

2.3. Perceived Technology Usefulness and Student Satisfaction

Within the Technology Acceptance Model, perceived usefulness is widely recognized as a key determinant of user evaluations. In educational environments, students who consider digital tools to be effective in supporting their learning processes tend to report higher levels of satisfaction with their academic experience.

Technological systems that facilitate learning activities, improve accessibility, and enhance efficiency contribute to more positive evaluations of educational programs. Therefore, perceived usefulness is expected to play an important role in shaping students' satisfaction levels.

H2: Perceived technology usefulness positively influences student satisfaction.

2.4. Perceived Technology Usefulness and Continuance Intention

Perceived usefulness is also closely associated with individuals' intentions to continue using a given system. In higher education settings, this intention can be reflected in students' willingness to persist in their current academic programs.

When students perceive technological infrastructure as supportive and effective, their motivation to continue their studies is likely to increase. Thus, perceived usefulness may indirectly contribute to student retention by strengthening continuance intention.

H3: Perceived technology usefulness positively influences continuance intention.

2.5. AI Integration Quality and Student Satisfaction

Students' perceptions of AI systems are strongly shaped by factors such as accuracy, fairness, and ethical appropriateness. These elements play a crucial role in building trust toward technological systems.

From a theoretical perspective, system quality is considered a fundamental antecedent of user satisfaction. When AI applications are perceived as transparent and reliable, students are more likely to develop trust, which in turn enhances their overall satisfaction with their educational experience.

H4: Perceived AI integration quality positively influences student satisfaction.

2.6. AI Integration Quality and Career Confidence

AI-supported learning environments have the potential to influence not only academic outcomes but also students' perceptions of their professional capabilities. Exposure to high-quality digital tools may enhance students' confidence in their readiness for future careers.

In particular, when AI systems are perceived as reliable, ethical, and well-integrated, students are more likely to trust the knowledge and skills they acquire, which may contribute to higher levels of career confidence.

H5: Perceived AI integration quality positively influences career confidence.

2.7. Student Satisfaction and Continuance Intention

Student satisfaction has consistently been identified as a critical determinant of persistence in higher education. Satisfied students are generally more engaged, more committed to their programs, and less likely to consider dropping out.

This suggests that satisfaction plays a central role in shaping students' decisions to continue their education.

H6: Student satisfaction positively influences continuance intention.

2.8. Continuance Intention and Career Confidence

Continuance intention reflects students' level of commitment to their educational journey. Students who demonstrate a strong intention to persist are more likely to develop positive expectations regarding their future careers.

This relationship indicates that academic persistence may contribute to the development of career-related confidence.

H7: Continuance intention positively influences career confidence.

2.9. Student Satisfaction and Career Confidence

Students who are satisfied with their academic experiences are more likely to believe that their education will help them achieve their professional goals. Satisfaction enhances not only academic engagement but also confidence in future career outcomes.

Therefore, student satisfaction is expected to exert a direct positive influence on career confidence.

H8: Student satisfaction positively influences career confidence.

As illustrated in Figure 1, the proposed model conceptualizes perceived technology usefulness as the primary exogenous construct, while perceived AI integration quality and student satisfaction function as mediating variables. Continuance intention and career confidence are positioned as key outcome variables.

By integrating perspectives from technology acceptance, student retention, and career development, the model offers a comprehensive framework that captures both direct and indirect relationships among constructs. Furthermore, incorporating ethical and transparency dimensions into AI integration quality provides a more nuanced understanding of AI applications in educational contexts.

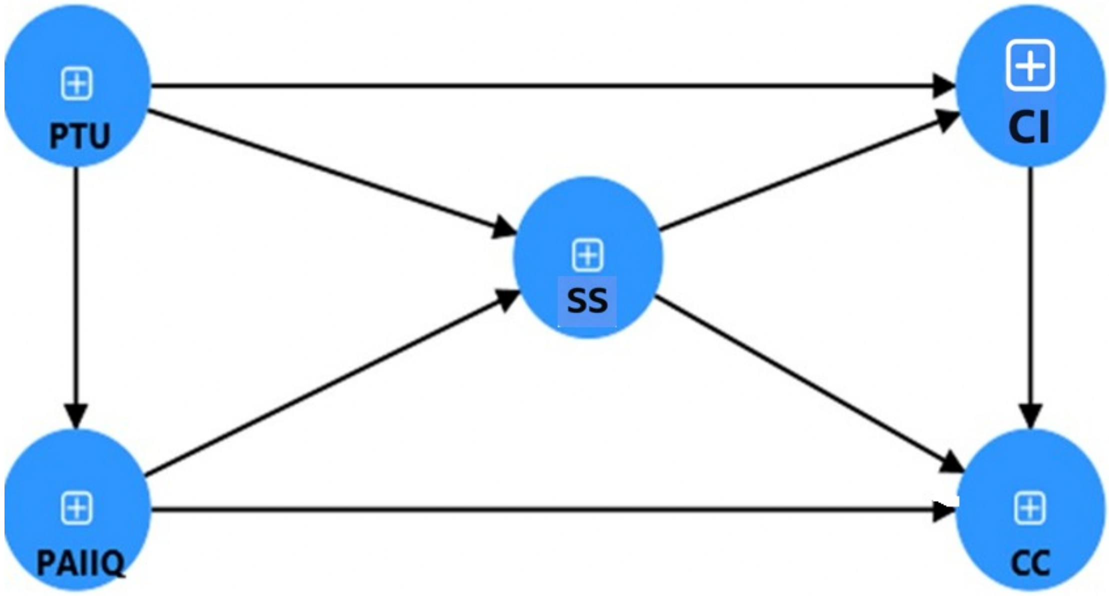

Figure 1. Research Model

Perceived Technology Usefulness (PTU), Perceived AI Integration Quality (PAIIQ), Student Satisfaction (SS), Continuance Intention (CI), Career Confidence (CC)

3. METHODOLOGY

3.1.Sample and Data Collection

The sample of this study consists of undergraduate and associate degree students enrolled in different universities across Türkiye. The study adopts a quantitative research design, and data were collected through an online survey method. A total of 250 responses were initially collected. After data screening and cleaning procedures, 236 valid responses were retained for the final analysis. The demographic characteristics of the participants are presented in Table 1. This cross-sectional survey design was selected because the study aims to test theoretically specified relationships among latent perceptions and attitudes at a single point in time rather than to evaluate an intervention or establish temporal causality.

Table 1.
Demographic Characteristics of Participants

Variable	Category	N	%
Gender	Female	140	59.3
	Male	96	40.7
Age	17–20	144	61.0
	21–24	83	35.2
	25 and above	9	3.8
Education Level	Undergraduate	207	87.7
	Associate Degree	29	12.3

The sample is predominantly composed of female students (59.3%), while male participants account for 40.7%. In terms of age distribution, the majority of respondents fall within the 17–20 age group (61.0%), followed by the 21–24 age group (35.2%). Participants aged 25 and above constitute a relatively small proportion (3.8%). Regarding educational level, 87.7% of the respondents are undergraduate students, while 12.3% are enrolled in associate degree programs. The sample includes students from a wide range of academic disciplines, demonstrating a heterogeneous structure. The highest participation rates are observed in Statistics (8.1%) and Medicine (7.6%), followed by Computer Engineering, Industrial Engineering, Midwifery, Electrical and Electronics Engineering, Visual Communication Design, and Primary Education. In terms of geographical distribution, the majority of participants are studying in Eskişehir (32.2%) and Kastamonu (16.5%), followed by Ankara (9.7%) and İzmir (8.1%). Although the sample reflects diversity across different regions and disciplines, the concentration in certain locations should be considered when interpreting the findings.

3.2.Measurement Instrument

Data for this study were obtained through a structured survey instrument designed to assess students' perceptions of technology and artificial intelligence, together with their academic attitudes and career confidence. All constructs were operationalized using multi-item scales measured on a five-point Likert continuum ranging from 1 (strongly disagree) to 5 (strongly agree). Perceived technology usefulness items were adapted from Davis (1989) and Venkatesh and Davis (2000). Student satisfaction and continuance intention items were adapted from the student retention and engagement formulations of Tinto (1993) and Thomas (2012). Career confidence items were adapted from social cognitive career theory and graduate career-readiness research (Lent et al., 1994; Jackson, 2014). Because no established scale captured the specific combination of accuracy, transparency, and ethical appropriateness in AI-supported higher education, the three perceived AI integration quality items were developed by the authors for this study, guided by Holmes et al. (2019), UNESCO (2021), and OECD (2023). The adaptation and development process involved reviewing each construct's conceptual domain, rewording items for AI-supported higher education, and checking item clarity through expert review before data collection.

The questionnaire was composed of five latent constructs:

Perceived Technology Usefulness (PTU)

This construct captures students' evaluations of the extent to which technological tools contribute to academic effectiveness and learning performance. Its four items were adapted from Davis (1989) and Venkatesh and Davis (2000) for AI-supported course settings. Sample item: "The technology I use for AI-supported course materials improves my learning effectiveness."

Perceived AI Integration Quality (PAIIQ)

This variable reflects students' perceptions of AI systems in terms of accuracy, transparency, and ethical appropriateness within the learning environment. The three items were newly developed by the authors for this study on the basis of the responsible-AI principles discussed by Holmes et al. (2019), UNESCO (2021), and OECD (2023); they were not taken verbatim from an existing scale. All three PAIIQ items are reported in Appendix A to improve measurement transparency.

Sample item: "AI applications generally produce reliable and accurate results."

Student Satisfaction (SS)

This construct represents students' overall evaluation of their academic experience and satisfaction with their chosen program. Its three items were adapted from Tinto (1993) and Thomas (2012).
Sample item: "Overall, I am satisfied with my choice of program."

Continuance Intention (CI)

Continuance intention refers to students' willingness to persist in their current academic program and continue their education. Its four items were adapted from Tinto (1993) and Thomas (2012).

Career Confidence (CC)

This construct assesses students' confidence in achieving future career goals following graduation. Its four items were adapted from Lent et al. (1994) and Jackson (2014). Sample item: "I am confident about finding a job after graduation."

The final questionnaire included 18 items: four items for perceived technology usefulness, three author-developed items for perceived AI integration quality, three adapted items for student satisfaction, four adapted items for continuance intention, and four adapted items for career confidence. No other items were newly developed. Content validity was supported through alignment with the cited theoretical definitions and expert review of item wording. Reliability and validity were empirically assessed through Cronbach's alpha, rho_A, composite reliability, AVE, HTMT, and the Fornell–Larcker criterion, as reported in the measurement model results.

3.3. Assessment of Common Method Bias

To address potential measurement bias, particularly common method variance, both procedural and statistical approaches were implemented.

As a procedural remedy, an attention-check item was embedded within the questionnaire to identify inattentive or inconsistent responses. Based on this criterion, 14 responses were removed from the dataset, thereby improving overall data quality.

From a statistical perspective, common method bias was examined using a separate full-collinearity assessment in which each latent construct was regressed on all remaining latent constructs. This procedure is distinct from the structural-model VIF values reported in Table 5. The full-collinearity VIF values were 1.982 for PTU, 1.920 for PAIIQ, 2.604 for SS, 2.624 for CI, and 2.201 for CC; all values are below the conservative threshold of 3.3 (Kock, 2015). Structural-model VIF values are reported separately in Table 5 and range from 1.000 to 2.483, indicating that predictor collinearity does not pose a concern in the structural paths.

Additionally, the measurement model was evaluated in terms of reliability and validity. Internal consistency was assessed using Cronbach's alpha and composite reliability (CR), while convergent validity was examined through average variance extracted (AVE). Discriminant validity was assessed using both the Heterotrait–Monotrait (HTMT) ratio and the Fornell–Larcker criterion. Following Fornell and Larcker (1981), Henseler et al. (2015), and Hair et al. (2022), HTMT values below 0.90 were treated as conservative evidence, whereas values below 0.95 were considered potentially acceptable for conceptually related constructs when corroborated by additional evidence.

Taken together, these findings indicate that the dataset is free from serious concerns related to common method bias or multicollinearity, and the measurement model demonstrates satisfactory psychometric properties.

4. RESULTS

4.1. Measurement Model Assessment

In this study, perceived AI integration quality is conceptualized as a standard first-order reflective perception of the quality of AI use in education. Accuracy, transparency, and ethical appropriateness are treated as related manifestations of an overall evaluation because students experience AI-supported systems as an integrated service encounter. PAIIQ is therefore not a higher-order construct, and the three facets are not modeled as separate lower-order dimensions.

The measurement model consists of five standard first-order reflective latent constructs: perceived technology usefulness (PTU), perceived AI integration quality (PAIIQ), student satisfaction (SS), continuance intention (CI), and career confidence (CC). PAIIQ is not modeled as a higher-order construct; its three indicators are reflective manifestations of one overall perception of AI integration quality. The measurement model was evaluated in terms of internal consistency reliability, convergent validity, and discriminant validity.

4.1.1. Internal consistency reliability and convergent validity

As shown in Table 2, all constructs demonstrate acceptable levels of internal consistency reliability. Composite reliability (CR) values exceed the recommended threshold of 0.70, indicating adequate internal consistency. The Cronbach's alpha value for PAIIQ ($\alpha = 0.659$) is slightly below the conventional 0.70 criterion, which should be interpreted cautiously because

PAIIQ is a newly developed three-item construct. However, its rho_A (0.773), CR (0.806), and AVE (0.589) are acceptable, supporting its use in this exploratory application.

Table 2.
Construct Reliability and Validity

Construct	CA	rho_A	CR	AVE
CC	0.786	0.821	0.861	0.611
SS	0.778	0.813	0.858	0.607
CI	0.798	0.797	0.871	0.630
PAIIQ	0.659	0.773	0.806	0.589
PTU	0.872	0.885	0.912	0.722

Note. CA = Cronbach's alpha; rho_A = reliability coefficient rho_A; CR = composite reliability; AVE = average variance extracted; CC = Career Confidence; SS = Student Satisfaction; CI = Continuance Intention; PAIIQ = Perceived AI Integration Quality; PTU = Perceived Technology Usefulness.

The findings reported in Table 2 indicate that all constructs demonstrate adequate levels of internal consistency, with composite reliability values exceeding commonly accepted criteria. Convergent validity was further evaluated by examining the extent to which each construct captures the variance of its indicators. In this regard, the average variance extracted (AVE) values surpass the recommended benchmark of 0.50, indicating that a substantial proportion of indicator variance is accounted for by their respective latent variables.

Moreover, the indicator loadings are both strong and statistically significant, suggesting that the measurement items provide a reliable representation of the underlying constructs. Taken together, these results provide sufficient evidence that the measurement model meets the necessary standards for reliability and convergent validity.

4.1.2. Discriminant validity (HTMT criterion)

Discriminant validity was evaluated using the Heterotrait–Monotrait (HTMT) ratio, as shown in Table 3. Most values are below the conservative 0.90 threshold. Two values—SS–CI and PTU–PAIIQ—are 0.902, marginally exceeding 0.90 but remaining below the more liberal 0.95 guideline for conceptually related constructs (Hair et al., 2022). These pairs should therefore be interpreted as borderline rather than unequivocal evidence of discriminant validity. Nevertheless, the Fornell–Larcker results in Table 4 provide corroborating evidence because each construct's square root of AVE exceeds its correlations with the other constructs. Taken together, the evidence supports acceptable, though cautious, discriminant validity for the two borderline pairs.

Table 3.
Discriminant Validity (HTMT Ratio)

Construct	CC	SS	CI	PAIIQ	PTU
CC	—				
SS	0.842	—			
CI	0.873	0.902	—		
PAIIQ	0.563	0.687	0.542	—	
PTU	0.523	0.568	0.503	0.902	—

Note. HTMT = Heterotrait-Monotrait ratio; CC = Career Confidence; SS = Student Satisfaction; CI = Continuance Intention; PAIIQ = Perceived AI Integration Quality; PTU = Perceived Technology Usefulness.

The HTMT results show that most construct pairs remain below 0.90. The SS–CI and PTU–PAIIQ ratios (both 0.902) marginally exceed the conservative cutoff and are therefore treated as borderline, although they remain below 0.95.

For the remaining construct combinations, HTMT values range between 0.503 and 0.873. The Fornell–Larcker results reported in Table 4 provide additional support for construct distinctiveness. Accordingly, discriminant validity is considered acceptable overall, with caution warranted for the two borderline HTMT pairs.

4.1.3. Discriminant validity (Fornell–Larcker criterion)

Discriminant validity was additionally examined using the Fornell–Larcker criterion, which evaluates whether each construct shares more variance with its own indicators than with other constructs. Accordingly, the square root of the AVE for each construct is expected to exceed its correlations with the remaining variables in the model.

Table 4.
Discriminant Validity (Fornell–Larcker Criterion)

Construct	CC	SS	CI	PAIIQ	PTU
CC	0.782				
SS	0.692	0.779			
CI	0.709	0.742	0.794		
PAIIQ	0.466	0.523	0.443	0.767	
PTU	0.461	0.470	0.438	0.733	0.849

Note. Diagonal values represent the square root of AVE. AVE = average variance extracted; CC = Career Confidence; SS = Student Satisfaction; CI = Continuance Intention; PAIIQ = Perceived AI Integration Quality; PTU = Perceived Technology Usefulness.

The results indicate that, for all constructs, the square root of AVE is greater than the corresponding inter-construct correlations, supporting the establishment of discriminant validity. For instance, the AVE square root of PTU (0.849) exceeds its correlations with the other variables. A similar pattern is observed for PAIIQ (0.767), CI (0.794), SS (0.779), and CC (0.782), further confirming that each construct is empirically distinct.

When considered together, the findings from both the HTMT analysis and the Fornell–Larcker criterion provide consistent evidence that the measurement model satisfies the requirements for discriminant validity.

4.1.4. Overall evaluation of the measurement model

Based on the reliability and validity assessments, the measurement model is considered statistically adequate. The results provide sufficient evidence to proceed with the structural model analysis.

4.2. Structural Model Assessment and Hypothesis Testing

Following the validation of the measurement model, the structural model was evaluated to test the hypothesized relationships among the constructs. The PLS-SEM analysis was conducted using SmartPLS 4, and the additional indirect-effect analysis was calculated from the retained SPSS dataset using 5,000 bootstrap resamples. Significance tests were interpreted as two-tailed tests. The structural-model results are summarized in Table 5, with explanatory power and indirect effects reported in Tables 6 and 7. Explanatory power was assessed using R^2 and adjusted R^2 values for all endogenous constructs, and predictive relevance was assessed using cross-validated Q^2 values.

Table 5.
Hypothesis Testing Results

Hypothesis	Path	Β	t-value	p-value	Decision	f²	VIF
H1	PTU → PAIIQ	0.733	23.682	<0.01***	Supported	1.164	1.000
H2	PTU → SS	0.187	2.503	<0.05**	Supported	0.023	2.164
H3	PTU → CI	0.115	1.721	<0.10*	Marginally supported	0.023	1.284
H4	PAIIQ → SS	0.385	5.160	<0.01***	Supported	0.097	2.164
H5	PAIIQ → CC	0.111	2.140	<0.05**	Supported	0.021	1.390
H6	SS → CI	0.688	15.167	<0.01***	Supported	0.839	1.284
H7	CI → CC	0.421	6.294	<0.01***	Supported	0.184	2.246
H8	SS → CC	0.322	4.757	<0.01***	Supported	0.098	2.483

Note: ***p < 0.01, **p < 0.05, *p < 0.10. β = standardized path coefficient; f^2 = effect size; VIF = structural-model variance inflation factor; PTU = Perceived Technology Usefulness; PAIIQ = Perceived AI Integration Quality; SS = Student Satisfaction; CI = Continuance Intention; CC = Career Confidence.

The significance of the proposed relationships was assessed using path coefficients, following current PLS-SEM reporting guidance (Yılmaz Uz, 2025) (β), t-statistics, and p-values. In addition, effect sizes (f^2) and variance inflation factor (VIF) values were examined to better understand the strength of the relationships and to detect potential multicollinearity issues. The VIF values, ranging from 1.000 to 2.483, remain well below both the conservative and commonly accepted thresholds, indicating that multicollinearity does not pose a concern in this model. Abbreviations used in Table 5 are as follows: PTU = Perceived Technology Usefulness;

PAIIQ = Perceived AI Integration Quality; SS = Student Satisfaction; CI = Continuance Intention; CC = Career Confidence; VIF = Variance Inflation Factor.

In addition to the path estimates, the explanatory and predictive power of the endogenous constructs and the indirect effects underlying the proposed mechanism were examined. These supplementary results are reported in Tables 6 and 7.

Table 6.
Explanatory and Predictive Power of Endogenous Constructs

Endogenous construct	R^2	Adjusted R^2	Q^2	Interpretation
PAIIQ	0.537	0.535	0.441	Moderate explanatory and predictive power
SS	0.289	0.283	0.210	Weak-to-moderate explanatory and predictive power
CI	0.561	0.557	0.552	Moderate explanatory and predictive power
CC	0.573	0.568	0.514	Moderate explanatory and predictive power

Note. R^2 and adjusted R^2 values indicate the variance explained in each endogenous construct. Q^2 values were obtained through 10-fold cross-validated prediction based on the retained SPSS dataset; positive Q^2 values indicate predictive relevance.

After assessing explanatory and predictive power, the indirect pathways were examined to clarify how technology usefulness and AI integration quality contribute to career confidence through satisfaction and continuance intention.

Table 7.
Indirect Effects Underlying the Proposed Mechanism

Indirect path	Standardized indirect effect	95% bootstrap CI	Interpretation
PTU → PAIIQ → SS	0.282	[0.083, 0.283]	Supported
PTU → SS → CI	0.129	[0.075, 0.276]	Supported
PAIIQ → SS → CC	0.124	[0.040, 0.158]	Supported
PAIIQ → SS → CI → CC	0.112	[0.031, 0.125]	Supported
SS → CI → CC	0.290	[0.178, 0.373]	Supported
PTU → PAIIQ → CC	0.081	[-0.025, 0.116]	Not supported
PTU total indirect effect on CC	0.417	[0.272, 0.470]	Supported
PAIIQ total indirect effect on CC	0.236	[0.079, 0.259]	Supported

Note. Indirect effects are standardized product effects calculated from the paths underlying the model. Bootstrap confidence intervals were obtained with 5,000 resamples of the retained SPSS dataset. Confidence intervals that do not include zero support the corresponding indirect pathway.

Regarding effect sizes, the results reveal substantial variation across relationships. In particular, the paths from SS to CI ($f^2 = 0.839$) and from PTU to PAIIQ ($f^2 = 1.164$) exhibit strong effects. The relationship between CI and CC ($f^2 = 0.184$) can be interpreted as moderate, whereas the remaining paths demonstrate relatively weaker effect sizes.

Perceived technology usefulness has a strong positive effect on perceived AI integration quality ($\beta = 0.733$, $t = 23.682$, $p < 0.01$), supporting H1. Its effect on student satisfaction is smaller but statistically significant ($\beta = 0.187$, $t = 2.503$, $p < 0.05$), supporting H2. The PTU → CI path is weak and reaches significance only at the 10% level ($\beta = 0.115$, $t = 1.721$, $p < 0.10$); H3 is therefore described as marginally supported rather than as equivalent to the more robust paths.

Perceived AI integration quality positively affects student satisfaction ($\beta = 0.385$, $t = 5.160$, $p < 0.01$) and career confidence ($\beta = 0.111$, $t = 2.140$, $p < 0.05$), supporting H4 and H5. This pattern indicates that AI-related perceptions primarily shape career outcomes indirectly through students' educational experience.

Student satisfaction has a strong positive effect on continuance intention ($\beta = 0.688$, $t = 15.167$, $p < 0.01$) and a direct positive effect on career confidence ($\beta = 0.322$, $t = 4.757$, $p < 0.01$), supporting H6 and H8. Continuance intention also contributes positively to career confidence ($\beta = 0.421$, $t = 6.294$, $p < 0.01$), supporting H7.

Regarding effect sizes, the paths from PTU to PAIIQ ($f^2 = 1.164$) and from SS to CI ($f^2 = 0.839$) show strong effects. The CI → CC path ($f^2 = 0.184$) represents a moderate effect, while the remaining relationships have smaller but meaningful effect sizes.

Overall, the findings support an indirect pathway through which perceived technology usefulness contributes to career confidence, operating through AI integration quality, student satisfaction, and continuance intention. The bootstrap confidence intervals reported in Table 7 provide additional support for the main indirect pathways, although the cross-sectional design still prevents causal mediation claims.

4.3. Importance–Performance Map Analysis

In this study, the Importance–Performance Map Analysis (IPMA), a valuable extension of PLS-SEM also referred to as importance–performance or priority map analysis, was employed. The IPMA matrix provides a comparative assessment of exogenous latent variables in terms of their importance and performance with respect to endogenous latent variables. The IPMA methodology evaluates the total effects (importance) of constructs on a selected target construct (endogenous latent variable) and compares these effects with the average latent variable scores (performance). The primary objective is to identify constructs that exert a strong total effect on the target variable but exhibit relatively low performance levels. Graphically, IPMA presents importance on the x-axis and performance on the y-axis, where performance scores are typically rescaled from 0 to 100. This representation allows for the simultaneous evaluation of the relative impact and performance of each construct. For interpretation purposes, particular attention is given to constructs located in the lower-right quadrant of the IPMA map. These constructs are characterized by high importance but low performance, indicating that they are critical areas requiring improvement. According to Ringle and Sarstedt (2016), such constructs represent high-priority targets for managerial interventions due to their strong potential for performance enhancement (Yılmaz and Arı, 2024). The resulting importance–performance map is presented in Figure 2.

Figure 2. Importance–Performance Map for Career Confidence

The IPMA findings highlight student satisfaction as the most influential factor in explaining career confidence (≈0.61), followed by continuance intention (≈0.42), perceived technology usefulness (≈0.41), and perceived AI integration quality (≈0.35).

In terms of performance, perceived technology usefulness demonstrates the highest score (≈78), with continuance intention also showing relatively strong performance (≈74). By comparison, student satisfaction (≈63) and perceived AI integration quality (≈64) remain at moderate levels. This pattern suggests that student satisfaction represents a key area for improvement, given its high importance combined with comparatively lower performance. Enhancing this construct is therefore likely to produce meaningful gains in career confidence.

Continuance intention, on the other hand, appears as a well-performing and highly influential factor, indicating that it constitutes a strength that should be preserved.

Although perceived technology usefulness achieves high performance scores, its contribution to career confidence is largely indirect. This implies that focusing solely on technological infrastructure may be insufficient, and that greater emphasis should be placed on how these technologies are integrated and experienced by students.

Similarly, perceived AI integration quality plays a more indirect yet strategically important role through its impact on student satisfaction. Improvements in the ethical, transparent, and pedagogically aligned use of AI systems may therefore contribute to career confidence by enhancing overall student experience.

Taken together, the IPMA results point to a layered influence mechanism, where technological factors affect career confidence primarily through satisfaction and engagement-related pathways. These insights offer practical guidance for higher education institutions in prioritizing strategic interventions and allocating resources effectively.

5. DISCUSSION AND CONCLUSION

5.1. Discussion of Findings

This study examined the effects of perceived technology usefulness and perceived AI integration quality on student satisfaction, continuance intention, and career confidence within a comprehensive structural model. The findings indicate that technological and AI-related perceptions influence student outcomes through distinct direct and indirect mechanisms. The strong effect of perceived technology usefulness on AI integration quality ($\beta = 0.733$) is consistent with TAM-based evidence that usefulness shapes favorable technology evaluations (Davis, 1989; Venkatesh & Davis, 2000). However, the much smaller PTU effects on satisfaction ($\beta = 0.187$) and continuance intention ($\beta = 0.115$, $p < 0.10$) show that usefulness alone provides limited explanatory leverage for broader educational outcomes. In contrast to conventional TAM studies that emphasize relatively proximal acceptance outcomes, the present results suggest that the consequences of usefulness become more substantial when transmitted through students' evaluations of AI integration and their academic experience.

One of the most notable findings is the strong effect of student satisfaction on continuance intention ($\beta = 0.688$). This result aligns with the student retention literature (Tinto, 1993; Thomas, 2012), emphasizing that satisfaction plays a central role in students' decisions to persist in their academic programs. In addition, the positive effects of satisfaction ($\beta = 0.322$) and continuance intention ($\beta = 0.421$) on career confidence support social cognitive career theory (Lent et al., 1994), indicating that positive academic experiences and sustained educational commitment can strengthen students' confidence in their future careers.

The relatively small direct effect of AI integration quality on career confidence ($\beta = 0.111$; $f^2 = 0.021$) indicates that responsible AI integration is supportive but not independently transformative for students' career beliefs. This pattern is consistent with recent empirical work showing that students recognize the educational potential of generative AI but remain concerned about accuracy, ethics, assessment, and overreliance (Chan & Hu, 2023; Roe et al., 2024; Pitts et al., 2025). Similarly, Altares-López et al. (2024) show that students' perceptions of AI in educational environments are connected to both learning support and career-related expectations, but these links depend on how AI is integrated pedagogically and ethically. Thus, accuracy, transparency, and ethical appropriateness appear to matter primarily because they improve the educational experience, not because they directly create confidence about employment or career success. Perceived technology usefulness has no direct path to career confidence in the specified model; its IPMA total effect (approximately 0.41) is therefore indirect, operating through AI integration quality, satisfaction, and continuance intention. The contrast between the small PAIIQ direct effect and the indirect PTU contribution underscores the layered mechanism proposed in this study and avoids attributing career confidence to technology exposure alone.

5.2. Theoretical Implications

This study offers three key theoretical contributions to the literature.

First, it extends the Technology Acceptance Model by integrating career confidence as a distal outcome variable. While prior research has primarily focused on usage intention and performance outcomes, this study demonstrates that the effects of perceived usefulness extend beyond immediate behavioral outcomes and operate indirectly through mediating variables.

Second, the study introduces perceived AI integration quality as a standard first-order reflective construct whose indicators capture accuracy, transparency, and ethical appropriateness as related manifestations of an overall quality perception. By linking this construct to student satisfaction and career-related outcomes, the study addresses an important gap in the literature and provides a more comprehensive understanding of AI in educational contexts.

Third, the findings challenge the commonly assumed direct relationship between technology use and positive outcomes. Instead, the study reveals an indirect and multi-layered pathway structure, where technological factors influence outcomes through experiential and psychological processes. This contributes to the growing body of literature that critiques technological determinism in education.

5.3. Managerial and Practical Implications

The findings of this study provide practical implications for higher education institutions, instructors, and policymakers.

First, student satisfaction emerges as the most critical determinant of career confidence. Therefore, universities should prioritize improving academic quality, strengthening faculty–student interaction, and enhancing the overall learning experience. For institutions, this means that investments should target the full student experience, including academic advising, accessible digital infrastructure, timely feedback, and high-quality interaction with instructors.

Second, the results highlight the importance of pedagogically aligned AI integration. Simply providing technological infrastructure is not sufficient; AI systems must be designed and implemented in ways that are ethical, transparent, and aligned with learning objectives. Recent empirical studies similarly show that students' acceptance of AI depends on perceived value, trust, assessment fairness, and appropriate reliance rather than on availability alone (Chan & Zhou, 2023; Roe et al., 2024; Pitts et al., 2025). For instructors, this implies that AI tools should be embedded into course design with clear pedagogical purposes, transparent explanations of how outputs are generated or used, and attention to fairness and student trust.

Third, the significant role of continuance intention suggests that student engagement and retention strategies are crucial. Initiatives such as mentoring programs, career counseling services, and industry collaborations can strengthen students' commitment and enhance their future career confidence. For policymakers, the results point to the need for institutional guidelines on ethical AI use, quality assurance, digital readiness, and career-oriented student support.

Finally, the findings indicate that investments in technology should be approached from a student experience perspective rather than a purely technical standpoint. Technological tools should be integrated in ways that enhance satisfaction and engagement, thereby indirectly contributing to career-related outcomes.

5.4. Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings.

First, the cross-sectional research design limits the ability to draw causal inferences. Future studies may employ longitudinal designs to examine how perceptions of technology and AI evolve over time. This limitation is particularly important because students' perceptions of AI may change rapidly as tools become more familiar and institutionally embedded.

Second, the data were collected through self-reported survey measures, which may be subject to social desirability and perceptual biases. Although procedural and statistical remedies were applied, such biases cannot be entirely eliminated. Future research could combine survey data with learning analytics, achievement indicators, or qualitative interviews to obtain a more comprehensive picture.

Third, the sample is limited to students within a specific national context. Future research should test the model across different countries and institutional settings to enhance generalizability. Replication in different national, disciplinary, and institutional contexts would help determine whether the proposed model is context-sensitive or broadly generalizable.

Finally, the model does not include certain variables that may influence career confidence, such as self-efficacy or academic performance. Future studies may incorporate additional constructs to provide a more comprehensive understanding of career-related outcomes. Future models may also examine digital literacy, trust in AI, perceived fairness, instructor support, employability skills, and academic self-efficacy as additional antecedents or moderators.

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Appendix

Table. Perceived AI Integration Quality Items

Item	English wording reported for transparency
PAIIQ1	AI applications generally produce reliable and accurate results.
PAIIQ2	I think the use of AI is ethical and fair.
PAIIQ3	AI tools provide concrete help in achieving my learning goals.

Note. The survey was administered in Turkish. The items above are English translations of the author-developed PAIIQ items.

Sena ÖZCAN KALFA

Orcid: 0000-0003-3704-2178

CONTACT DETAILS

E-mail: senaozcan88@gmail.com
Address: Ministry of National Education, Denizli, Türkiye

BIOGRAPHY

Sena Özcan Kalfa received her bachelor’s degree in Psychology from Ege University in 2010. She completed her master’s degree in Psychological Counseling and Guidance at Pamukkale University in 2016 and her PhD in the same field at Anadolu University in 2023. Her research interests include educational technologies, artificial intelligence in education, student well-being, career development, and psychological counseling.