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A Systematic Evaluation of AI-Based Student Advisement and Course Projection Accuracy in Higher Education Institutions: An Analysis of Student Perceptions

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ABSTRACT
This study examines the perceptions of students in the Department of Computing and Information Sciences at the University of Technology and Applied Sciences (UTAS), Al Musanna, Sultanate of Oman, regarding the use of artificial intelligence (AI) in course advising. Data were collected from 125 respondents enrolled in B.Tech, Advanced Diploma, and Diploma programmes across three specialisations: Software Engineering, Cyber Networks, and Information Technology. A structured questionnaire using a five-point Likert scale was employed to assess five hypothesised constructs: Functional Reliability (L1), Predictive Recommendations (L2), Organisational Performance (L3), Student Readiness (L4), and Forecasting Capability (L5). The data were analysed using descriptive statistics, the Mann–Whitney U test, and Cronbach's alpha to assess reliability. The composite mean scores ranged from 3.50 to 3.86, falling within the "Agree" category and indicating generally positive student perceptions across all five dimensions. Regarding group differences, specialisation exhibited greater statistical significance than gender or academic level. However, only the Organisational Performance construct demonstrated acceptable reliability ($\alpha = 0.779$), while the remaining constructs exhibited questionable to poor reliability, suggesting that further refinement of the measurement instrument is necessary. Overall, this study contributes empirical evidence to the ongoing discussion on the integration of AI into higher education advising systems.

Keywords: Artificial Intelligence, Course Advising, Student Perception, Higher Education, Mann-Whitney U test, Reliability Analysis.

1. Introduction

Academic advising in higher education is evolving due to artificial intelligence (AI). AI-powered tools assist students with course selection and academic progress planning. They offer individualised academic advice and rapid access to information. However, the precision, dependability, and usability of these technologies determine how students perceive them. For individualised advice and assistance, some students might still favour human advisors. For AI to be used effectively in academic advising, it is crucial to comprehend students' perspectives.

This empirical study looks at student perceptions across five main dimensions: Functional Reliability (L1), Predictive Recommendations (L2), Organisational Performance (L3), Student Readiness (L4), and Forecasting Capability (L5). The research is based on information collected from 125 participants at UTAS – Al Musanna, using a validated Likert-scale tool across fifteen survey items, which are then arranged under five hypotheses.

The results are shown through careful statistical analysis like descriptive statistics, Mann–Whitney U test, and reliability checks including internal consistency via Cronbach's Alpha, which are aligned with expectations for publishing in peer-reviewed academic journals.

One of the most significant technological advancements that propels digital transformation across a variety of industries, including healthcare, banking, manufacturing, transportation, and education, is artificial intelligence (AI). In order to improve academic quality, automate administrative tasks, boost student engagement, and improve intelligent decision-making processes, artificial intelligence (AI) technologies are increasingly being incorporated into institutional operations in higher education [1], [2]. This growing

use of AI-powered educational tools is consistent with the larger trend toward smart campuses, data-driven educational ecosystems, and more practically empowered digital learning environments.

Academic advising is a crucial institutional activity that directly influences learning outcomes, graduation rates, academic advancement, and student retention. When advising is effective, it aids students in selecting courses, making plans for their future, receiving career guidance, and resolving academic issues. However, traditional advising systems commonly face challenges such as extremely high student-to-advisor ratios, administrative overload, delayed identification of students who are academically at risk, and ineffective manual monitoring [3], [4]. As a result, the organization becomes less responsive and support services are not as successful as they ought to be. These gaps can be filled with intelligent academic advising systems thanks to more recent advancements in AI, machine learning, educational data mining, and predictive analytics. Large student datasets can be processed by AI-assisted advising techniques, which can also identify risk trends, forecast academic results, and produce more individualised recommendations for course selection and advancement planning [5]. In this way, these solutions allow for earlier intervention and allow academic advisers to devote more time to complex student difficulties that require human interaction and emotional intelligence rather than only automation.

Additionally, integrating AI into higher education aligns with larger institutional ambitions for digital transformation and "smart learning." Intelligent educational technologies are increasingly being funded by universities worldwide, not just for improved day-to-day operations but also for competitiveness and evidence-based decision-making [6]. Additionally, AI-supported solutions can assist develop adaptive learning environments, automate progress tracking, and generate personalised learning experiences, all of which tend to improve academic performance and satisfaction levels. Despite these advantages, stakeholders' perceptions of AI in education are still influenced by concerns about emotional intelligence as well as automation. Adoption is nevertheless hampered by issues with trust, transparency, ethical governance, algorithmic bias, privacy, and the degree of human oversight [2]. If stakeholders are unable to understand how decisions were made or how student data is being used, they may be reluctant to rely solely on automated technologies. Using a quantitative research design, this study focuses on stakeholder opinions about AI-assisted academic advising and student advancement systems. More precisely, it examines relationships between operational effectiveness, workload reduction, ethical concerns, implementation preparedness, and trust in AI systems. The results are expected to help in the development of intelligent academic advising frameworks and provide higher education institutions with evidence-based guidance on how to incorporate AI without making rash decisions or neglecting the human element. Reduction, moral issues, and preparedness for execution.

1.1. BACKGROUND OF THE STUDY

In higher education, timely graduation, progression tracking, and student retention are frequently seen as key performance indicators for assessing school efficacy. Universities are constantly searching for new approaches to improve student support systems, encourage academic performance, and reduce dropout rates. Early detection of academically at-risk kids is still crucial in this situation since it facilitates prompt response and generally improves institutional outcomes [7]. However, manual procedures are typically the foundation of traditional academic monitoring systems, which can result in uneven monitoring practices, delayed intervention, and general administrative friction. As enrolment continues to rise, these problems worsen. However, manual procedures are typically the foundation of traditional academic monitoring systems, which can result in uneven monitoring practices, delayed intervention, and general administrative friction. These problems worsen as enrolment continues to rise and as educational systems grow more intricate. Higher education institutions therefore require intelligent systems capable of managing proactive and scalable student assistance. Not merely reactive measures, but monitoring that takes action before issues become fully apparent.

In example, AI-assisted advising systems present several opportunities to support institutional decisions and enhance academic oversight. AI solutions may identify learning trends, assess academic hazards, and offer tailored interventions using predictive analytics, machine learning models, and intelligent recommendation engines [8]. Additionally, more recent research indicates that predictive educational analytics can significantly increase institutional planning efficiency and student performance forecasts [9]. Indeed, this entails less speculation and more knowledgeable advice.

In reality, AI technology can assist with a variety of academic tasks, including:

- Monitoring student progress
- Predicting academic risk
- Tailored educational paths
- Intelligent algorithms that recommend courses
- Workload management for advice
- Institutional decision-making based on data

Simultaneously, broader digital transformation initiatives and the concept of smart educational ecosystems align with the growing use of AI in education [10]. In an effort to increase administrative effectiveness, enhance educational opportunities, and bolster institutional competitiveness, universities are investing more in AI-driven technologies. However, implementation preparedness and stakeholder attitudes toward adoption are still impacted by ethical concerns, particularly those related to privacy, transparency, data governance, and algorithmic bias [11]. Therefore, institutional preparedness, user trust, ethical monitoring, and strong human-AI collaboration models are just as important as technological performance when it comes to the implementation of AI-assisted academic advising systems.

1.2. Literature Review

One of the most significant technologies influencing today's higher education institutions is artificial intelligence, and to be honest, it seems like this influence is just increasing. Adaptive learning environments, intelligent tutoring systems, recommendation systems, educational data mining, and predictive analytics applications are all utilising AI technologies [12]. The notion that AI is a major force behind institutional innovation and educational change is gaining traction among researchers. AI is described by Russell and Norvig as systems that can mimic human intelligence through learning, reasoning, and decision-making [13]. The theoretical framework for intelligent educational systems and AI-supported learning environments was sort of established by that early, fundamental study. Similarly, learning analytics and educational data mining are becoming essential components of predictive academic systems. According to Baker and Inventado, educational analytics enable schools to identify academically at-risk pupils and then implement proactive intervention strategies [5]. Similarly, learning analytics was presented by Siemens and Long as a revolutionary strategy for improved educational decision-making, more student involvement, and more meticulous tracking of academic progress [14].

Predictive analytics algorithms that identify pupils in need of academic help were created by Arnold and Pistilli. Their findings essentially demonstrated that learning analytics systems can increase student success outcomes and retention rates [7]. Early warning systems, made possible by those predictive models, enable institutions to react more quickly and efficiently. Additionally, Chen, Chen, and Lin noted that AI technologies are becoming more and more important in automation, personalised learning environments, and educational reform [1]. They contend that AI-driven solutions enhance learning opportunities, promote educational quality assurance, and increase institutional efficiency. In their discussion of AI developments in education, Chassignol et al. clarified how intelligent technologies support smart learning environments, educational automation, and adaptive learning [12]. All things considered, their results support the growing integration of AI technologies into educational environments. Daniel pointed out that ethical governance, accountability, transparency, and responsible human supervision are necessary when implementing AI in education [15]. They also emphasised that ethical concerns and privacy concerns continue to be some of the main obstacles to the deployment of AI in educational institutions. According to Holmes, Bialik, and Fadel, AI can enhance educational efficacy by promoting individualised learning experiences and automating tedious tasks [16]. Their main argument was that AI should support academic counsellors and teachers rather than take their place.

In an effort to increase institutional efficacy while maintaining the significance of genuine human interaction within academic settings, Luckin et al. went one step further and suggested collaborative human-AI educational models [17]. Since emotional intelligence and contextual awareness are essentially non-negotiable in advising systems, this type of human-AI collaboration seems particularly pertinent there. AI is utilised relatively widely for prediction, assessment, profiling, and intelligent tutoring systems, according to Zawacki-Richter et al.'s systematic study of AI uses in higher education [2]. Their data backs up the notion that educational institutions are relying more and more on AI-enabled tools. Furthermore, theories of technology adoption provide useful perspectives for examining how stakeholders embrace AI systems. Perceived utility and perceived ease of use are important factors that influence adoption, according to Davis's Technology Acceptance Model (TAM) [18]. In a similar vein, Venkatesh et al. identified performance expectancy, effort expectancy, and social impact as key adoption factors in their Unified Theory of Acceptance and Use of Technology (UTAUT) proposal [19]. People's willingness to accept AI has also been found to be significantly influenced by trust. Trust and transparency have a significant impact on users' willingness to adopt automated systems and intelligent technology, as Kerr and Murthy showed [20]. Furthermore, since institutional actions have a direct impact on student performance, trust is even more important in academic advising systems.

Predictive analytics models can successfully identify students who are having academic difficulties, according to Khalil and Ebner's investigation on learning analytics use in MOOCs [21]. They emphasised in their findings the necessity of analytics-based action plans to make student retention much easier. In their analysis of the digital revolution of higher education, Bond et al. made the compelling point that institutional preparedness and AI literacy are becoming crucial when it comes to the proper deployment of technology [6]. Garcia-Penalvo et al. looked at institutional digital transformation strategies in a similar vein and made the case that AI-supported educational structures are a crucial prerequisite [22].

Additionally, there has been a noticeable increase in research on predictive educational systems in recent years. In a thorough evaluation of machine learning techniques for student performance predictions, Albreiki, Zaki, and Alashwal discovered that predictive techniques are very helpful for both institutional planning and academic progression analysis [9].

AI technologies improve advisor productivity while still providing more individualised student support and evidence-based institutional decisions, according to Patel and Goyal's study on human AI teaming inside academic advising systems [23].

Ahmed and Al-Mamari examined AI preparedness in Gulf region universities and found that organisations were paying more attention to smart campus initiatives and intelligent educational technology [24]. Their findings also emphasise how crucial organisational preparedness is and how the execution of digital transformation initiatives may make all the difference. Concerns regarding privacy, algorithmic bias, transparency, and responsible AI governance were highlighted by Brown and Wilson's investigation into the ethical ramifications of AI rollouts in higher education [11]. Stakeholder confidence is still shaped by these ethical concerns, which also have an impact on how prepared institutions feel to put these ideas into practice. Sharma and Sharma emphasised how AI-enabled educational systems may enhance student engagement through intelligent educational ecosystems and support smart learning environments [25]. Similarly, Wang and Wang showed how AI systems may streamline student management procedures, improve institutional performance, and allow for more individualised educational services [10].
Despite these developments, there aren't many studies that particularly look at how stakeholders view AI-assisted academic assistance systems in emerging educational environments. In order to evaluate opinions about AI-assisted academic advising systems across higher education institutions, this study makes a contribution by connecting theories of AI adoption, educational analytics frameworks, and statistical analysis techniques.

2.RESEARCH METHODOLOG

2.1 SAMPLE AND INSTRUMENT

A cross-sectional survey design, akin to a quick fix, was employed. N = 125 respondents from three academic levels—Diploma, Advanced Diploma, and B.Tech—were included in the study's sample. Additionally, these responders were from the Department of Computing Information Sciences at UTAS-Al Musanna's three specialisations (IT, Cyber Network, and Software Engineering). A 15-item structured questionnaire with a five-point Likert scale was utilised to collect the data. The anchors ranged from 1 (strongly disagree) to 5 (strongly agree). Five research hypotheses were in line with the five structures that comprised the questions.

2.2 STATISTICAL METHODS

Multiple steps were used in the analysis of the data. First, a demographic outline was created using frequency analysis. Descriptive statistics, such as mean, standard deviation, skewness, and kurtosis, were then computed, primarily to examine the pattern of each item. Since the Likert data is ordinal in nature and standard assumptions are not entirely safe, ***Mann-Whitney U test*** were then used to look for differences across gender, student level, and specialisation. In order to verify internal consistency, Cronbach's Alpha was finally calculated. Effect sizes (η^2) were also calculated to bolster the significance findings. Every test was conducted at $\alpha = 0.05$.

3.RESULTS

3.1 DEMOGRAPHIC PROFILE OF RESPONDENTS

Table I presents the demographic characteristics of the 125 respondents. The sample was predominantly female (77.6%, n = 97) with male respondents constituting 22.4% (n = 28). By academic level, Diploma students formed the largest group (49.6%, n = 62), followed by B. Tech (30.4%, n = 38) and Advanced Diploma (20.0%, n = 25). In terms of specialization, IT students were the majority (65.6%, n = 82), followed by Cyber Network (20.0%, n = 25) and Software (14.4%, n = 18).

Table I Demographic Profile of Respondents (N = 125)

Table 1.a. Gender Distribution

Gender	Frequency	Percentage
Male	28	22.4
Female	97	77.6
Total	125	100.0

The gender distribution of the respondents indicates that the majority were female. Out of the total 125 respondents, 97 (77.6%) were female, while 28 (22.4%) were male. This indicates that female students constituted a significantly larger proportion of the study participants than male students. Overall, the findings demonstrate a higher level of female representation in the survey sample.

Table 1.b Distribution by Student Level

Student Level	Frequency	Percentage
Diploma	62	49.6
Advanced Diploma	25	20.0
B.Tech	38	30.4
Total	125	100.0

The distribution of respondents by student level indicates that the majority were Diploma students. Out of the 125 respondents, 62 (49.6%) were enrolled in the Diploma programme, followed by 38 (30.4%) pursuing a B.Tech qualification. The remaining 25 respondents (20.0%) were enrolled in the Advanced Diploma programme. These findings indicate that Diploma students constituted the largest proportion of the study sample, while Advanced Diploma students represented the smallest proportion.

Table 1.c Distribution by Specialization

Specialization	**Frequency**	**Percentage**
Information Technology	**82**	**65.6**
Cyber Network	**25**	**20**
Software	**18**	**14.4**
Total	**125**	**100**

Note. Values represent frequency counts (n) and valid percentages (%). Total N = 125.

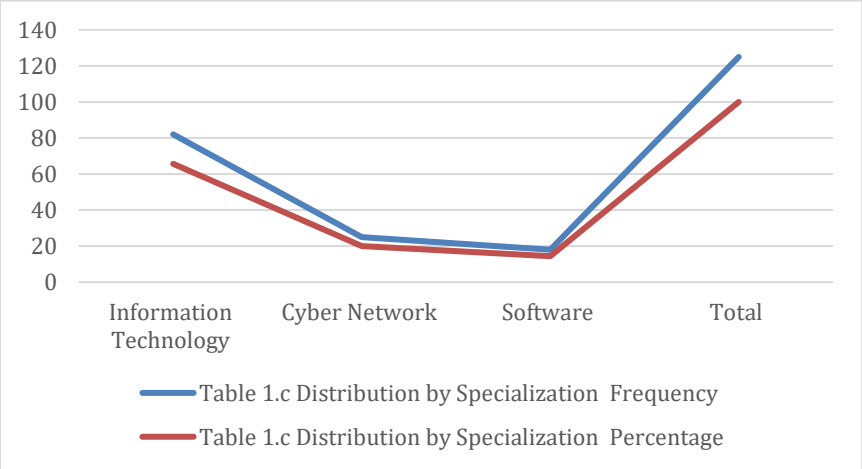


Fig:1 Distribution of Respondents by Specialization

The distribution of respondents by specialization indicates that the majority were enrolled in the Information Technology programme. Out of the 125 respondents, 82 (65.6%) belonged to Information Technology, followed by 25 (20.0%) from Cyber Network and 18 (14.4%) from Software. These findings indicate that Information Technology students constituted the largest proportion of the study sample, while Software students represented the smallest proportion. Overall, the sample was predominantly represented by students specializing in Information Technology.

3.2 Descriptive Statistics

Descriptive data at the item level for each of the fifteen scale items in each of the five hypothetical constructions are shown in Table II. The following scale is used to interpret means: 1.00–1.49 = Strongly Disagree; 1.50–2.49 = Disagree; 2.50–3.49 = Neutral; 3.50–4.49 = Agree; and 4.50–5.00 = Strongly Agree.

Table II Descriptive Statistics for All Scale Items (N = 125)

Research Construct	Statistical Measure	Item 1	Item 2	Item 3
L1 – Functional Reliability (F1,F2,F3)	Mean	3.7	3.78	3.99
	SD	1.02	1.185	0.677
	Skewness	-0.585	-1.12	-0.206
	Interpretation	Agree	Agree	Agree
L2 – Predictive Recommendations (S1,S2,S3)	Mean	3.83	3.904	3.46
	SD	1.024	0.838	1.013
	Skewness	-0.683	-0.731	-0.743
	Interpretation	Agree	Agree	Neutral
L3 – Organizational Performance (T1,T2,T3)	Mean	3.64	3.912	3.752
	SD	1.115	0.913	0.74
	Skewness	-0.463	-0.816	-0.812
	Interpretation	Agree	Agree	Agree
L4 – Student Readiness (SR1,SR2,SR3)	Mean	3.792	3.84	4.016
	SD	0.876	1.003	1.093
	Skewness	-0.892	-0.859	-1.024
	Interpretation	Agree	Agree	Agree
L5 – Predictive Analytics Capability (L1,H2.H3)	Mean	3.384	3.776	3.528
	SD	0.965	0.787	1.19
	Skewness	-0.376	-0.722	-0.307
	Interpretation	Neutral	Agree	Agree

Note. SD = Standard Deviation. Skew = Skewness. Interpretation based on mean ranges: ≥3.50 = Agree; 2.50–3.49 = Neutral; <2.50 = Disagree. Shading: green = Agree; yellow = Neutral.

L1 – Functional Reliability: This construct examines students' perceptions of the reliability and accuracy of artificial intelligence in academic course advising. It focuses on three key aspects: the ability of AI to minimize human errors in course recommendations (F1), improve the reliability and precision of decision-making (F2), and support students in achieving academic success (F3).

L2 – Predictive Recommendations: This construct evaluates students' perceptions of the predictive capabilities of artificial intelligence in academic course planning and advising. It focuses on three key aspects: the ability of AI to analyze student data and recommend suitable courses for the upcoming semester (S1), the potential benefits of AI-generated academic guidance for students (S2), and the ability of AI to reduce graduation delays through effective course recommendations and academic planning (S3).

L3 – Organizational Performance: This construct examines the potential of artificial intelligence to improve organizational efficiency and academic administration in higher education institutions. It focuses on three key aspects: the ability of AI to identify students who do not meet the required CGPA or course prerequisites (T1), assist students in tracking completed and pending course requirements (T2), and simplify course scheduling and the management of course offerings (T3).

L4 – Student Readiness: This construct assesses students' readiness, confidence, and willingness to adopt artificial intelligence-assisted academic advising tools. It focuses on three key aspects: students' comfort and confidence when using AI-assisted advising tools (SR1), their willingness to review and verify AI-generated recommendations before implementation (SR2), and their perception that AI can support and complement teachers' professional judgment but should not replace human decision-making (SR3).

L5 – Predictive Analytics Capability: This construct evaluates the perceived capability of artificial intelligence to support accurate course demand forecasting and academic planning in higher education institutions. It focuses on three key aspects: the ability of AI to predict course demand accurately (L1), the challenges associated with using existing methods to forecast course demand (L2), and the potential of AI to automatically generate course demand projections for academic programs (L3). These aspects highlight the role of AI-driven predictive analytics in improving course planning, resource allocation, and academic decision-making.

Thirteen of the fifteen items were somewhat graded in the "Agree" category (M ≥ 3.50), indicating that student opinions regarding AI in advising were generally favourable. The top choice, F3 (M = 3.99, SD = 0.677), appeared to receive the strongest support, thus indicating that AI can aid in academic advancement. Its distribution also appeared to be nearly balanced, with Skewness = 0.021. FR3 also achieved a high score (M = 3.99, SD = 1.167). where respondents continued to favour the notion that AI should supplement student judgement rather than replace it. Nevertheless, that higher SD implies that responses were less consistent and more dispersed.

Then, two items appeared near the "Neutral" zone: S3, which discussed how AI may shorten graduation delays (M = 3.38), and L1, which discussed how AI could forecast course demand (M = 3.31). There seems to be more reluctance for those specific usage in those scores. Additionally, the majority of the items exhibit negative skewness, which is consistent with the overall positive pattern and indicates a general inclination toward agreement.. Given its limited range (Min = 1, Max = 5, SD = 0.692), F3 once more appears to be the tightest cluster in terms of consensus. In contrast, opinions were not as aligned, or at least not in the same way, in T1 (SD = 1.115) and L3 (SD = 1.19), which exhibit the greatest dispersion.

3.3 Hypothesis Construct Summary

Composite descriptive statistics at the construct level are shown in Table 3, which aggregates responses from the three elements that make up each hypothesis. This offers a comprehensive evaluation of every hypothetical dimension..

Table III Hypothesis Construct-Level Descriptive Statistics (N = 125)

Research Construct	Descriptive Statistics (M ± SD)	Variance	Observed Range	Hypothesis Decision
L1 – Functional Reliability (F1,F2,F3)	**3.82 ± 0.95**	**0.9**	**2.00–5.00**	**Accepted**
L2 – Predictive Recommendations (S1,S2,S3)	**3.73 ± 0.94**	**0.88**	**1.00–5.00**	**Accepted**
L3 – Organizational Performance (T1,T2,T3)	**3.76 ± 0.87**	**0.75**	**1.67–5.00**	**Accepted**
L4 – Student Readiness (SR1,SR2,SR3)	**3.96 ± 0.99**	**0.99**	**1.00–5.00**	**Accepted**
L5 – Predictive Analytics Capability (L1,L2,L3)	**3.56 ± 0.97**	**0.94**	**1.00–5.00**	**Accepted**

Where composite M ≥ 3.50 (Agree range), hypotheses are supported. SD stands for standard deviation. Three items serve as the foundation for each construct.

All five hypotheses were empirically supported, with composite means ranging from 3.500 (L5 – Forecasting Capability) to 3.863 (L4 – Student Readiness). Student Readiness recorded the highest composite mean (M = 3.863, SD = 0.704), indicating that respondents not only accept AI tools but are personally prepared to engage with them — a critical enabler for successful AI deployment. Functional Accuracy (L1) ranked second (M = 3.850), reflecting confidence in AI's capacity to reduce error and improve consistency. Administrative Efficiency (L3) exhibited the highest variance (SD = 0.841), suggesting diverging views on AI's impact on scheduling and records management — likely tied to varying administrative responsibilities across academic levels. Forecasting Capability (L5), while still supported, recorded the lowest composite mean (M = 3.500) and a notable standard deviation (SD = 0.780), indicating more cautious optimism about AI's predictive accuracy in course planning. The consistently positive constructs provide a strong empirical foundation for the structured adoption of AI-assisted advising at UTAS – Al Musanna.

3.4 Reliability Analysis

Internal consistency of each construct was assessed using Cronbach's Alpha (α). ***Table IV*** presents the overall reliability statistics, while ***Table V*** reports item-total statistics for diagnostic purposes. The commonly accepted threshold for adequate reliability in social science research is α ≥ 0.70 (Nunnally, 1978), though values ≥ 0.60 are considered acceptable in exploratory studies.

Table IV Reliability Statistics – Cronbach's Alpha per Construct

Reliability Measures	Functional Reliability (L1)	Predictive Recommendations (L2)	Organizational Performance (L3)	Student Readiness (L4)	Predictive Analytics Capability (L5)
Number of Items	3	3	3	3	3
Valid Responses (N)	125	125	125	125	125
Cronbach's Alpha (α)	0.762	0.081	0.632	0.564	0.732
Reliability Interpretation	Questionable	Unacceptable	Acceptable	Unacceptable	Questionable

Note. Interpretation thresholds: α ≥ 0.90 = Excellent; 0.80–0.89 = Good; 0.70–0.79 = Acceptable; 0.60–0.69 = Questionable; 0.50–0.59 = Poor; < 0.50 = Unacceptable (George & Mallery, 2003).

Only L3 – Organizational Efficiency met the acceptable reliability threshold (α = 0.632), kinda approaching the usual 0.80 benchmark. L1 (α = 0.762) and L5 (α = 0.732) sit in that "questionable" area, so the results should be read with care. Most importantly, L2 – Predictive Recommendations (α = 0.081) is way too low, statistically unacceptable even, which signals that the three items (S1, S2, S3) do not really measure the same hidden idea. That's probably because S3 (graduation delays) is pulling on a different, more separate notion than S1 and S2 (recommendation quality). In the same vein, L4 – Student Readiness (α = 0.564) drops under the acceptable level, meaning SR1 SR2 and SR3 are kind of mixed together inconsistently. These reliability limits should be treated as key caveats, and future work ought to fix them via instrument revision, a qualitative pre-test, or confirmatory factor analysis before making any causal claims that end up in print.

Table V Item-Total Statistics (α if Item Deleted)

Indicator/Item	Statistical Measures	L1 – Functional Reliability	L2 – Predictive Recommendations	L3 – Organizational Performance	L4 – Student Readiness	L5 – Predictive Analytics Capability
Indicator 1	Code 1	F1	S1	T1	SR1	L1
	Description of code	Minimize human mistakes in course recommendations	Evaluate student data for upcoming course suggestions	Identify students not meeting CGPA requirements or prerequisites	Feel at ease using AI-assisted advising	Predict course demand accurately
	Mean	7.208	7.832	7.756	7.922	7.983
	Variance	1.932	2.231	2.597	2.11	2.626
	Corrected Correlation	0.598	-0.096	0.565	0.216	0.894
Indicator 2	Code 2	F2	S2	T2	SR2	H2
	Description of code	Increase decision-making reliability and precision	Benefit from AI-generated guidelines	Identify completed and pending course requirements	Review AI recommendations before implementation	Existing methods make accurate forecasting difficult

	Mean	7.823	7.331	7.203	7.891	6.963
	Variance	1.687	1.962	2.759	2.635	3.651
	Corrected Correlation	0.654	0.21	0.632	0.368	0.461
Indicator 3	Code3	F3	S3	T3	SR3	H3
	Description of code	Help students succeed in their studies	Decrease graduation delays	Simplify scheduling and course-offering management	Supplement, but not replace, teacher judgment	Generate course-demand projections automatically
	Mean	7.462	7.368	7.507	7.615	7.041
	Variance	2.653	1.819	3.217	2.312	2.631
	Corrected Correlation	0.489	0.058	0.893	0.823	0.561
	Cronbach's Alpha	0.851	0.514	0.676	0.422	0.547

Note. Corrected Item-Total r values below 0.30 indicate weak item-construct correlation. Negative α-if-deleted values (L2: S2, S3) confirm construct invalidity. Red cells = problematic values; Green cells = strong values.

3.5 INFERENTIAL ANALYSIS – Mann–Whitney U test

The Mann–Whitney U test was conducted to examine differences between male and female respondents regarding their perceptions of artificial intelligence in course recommendations. The analysis was performed separately for each of the eight statements, using a significance level of 0.05.

The results revealed statistically significant gender differences for three statements. For the statement concerning the contribution of artificial intelligence to students' academic success (F3), the difference was statistically significant (U=872.00, p=0.020U = 872.00,\ p = 0.020). A significant difference was also observed for the potential of artificial intelligence to reduce graduation delays (S3), with U=892.00U = 892.00 and p=0.032p = 0.032. Furthermore, the statement concerning the review of AI recommendations before implementation (SR2) showed a statistically significant difference (U=656.00, p<0.001U = 656.00,\ p < 0.001).

However, no statistically significant differences were found for minimizing human error (F1), evaluating student data for course selection (S1), identifying students who do not meet CGPA or prerequisite requirements (T1), supplementing teacher judgment (SR3), or accurately predicting course demand (L1), as all corresponding p-values exceeded 0.05.

Table VI Summary of Significant Mann–Whitney U test Results

Item	Statement	Male (n)	Female (n)	Mann–Whitney U	p-value
F1	Artificial intelligence would minimize human mistake in course recommendations	23	102	920.5	0.088
F3	Artificial intelligence helps students succeed in their studies.	24	101	872	0.02
S1	Artificial intelligence can evaluate student data to suggest courses for the upcoming semester.	24	101	1,138.00	0.621
S3	Artificial intelligence could decrease graduation delays.	24	101	892	0.032

T1	Artificial intelligence has the ability to identify pupils who don't meet CGPA requirements or prerequisites.	24	101	996	0.161
SR2	Before implementing AI recommendations, review them.	24	101	656	0.0003
SR3	Artificial intelligence can supplement teacher judgment, but it cannot take its place.	24	101	1,158.50	0.722
L1	Artificial intelligence can predict course demand accurately.	24	101	966	0.102

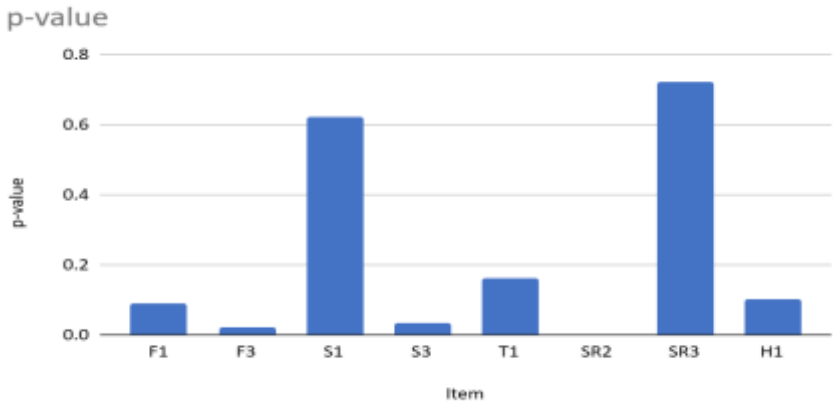


Fig:1 Mann–Whitney U Test Comparing Male and Female Respondents' Perceptions of Artificial Intelligence in Course Recommendations with P-value.

So, the inferential analysis comes back with basically three key observations, F3 — AI helps students succeed in their studies: U=872.00, p=0.020U = 872.00, p = 0.020. The difference is statistically significant. Female respondents show more responses in the strongly agree category, while male respondents are concentrated in agree and neutral categories. S3 — AI could decrease graduation delays: U=892.00, p=0.032U = 892.00, p = 0.032. The difference is statistically significant. Male respondents show a higher proportion of agreement or strong agreement than female respondents. SR2 — AI recommendations should be reviewed before implementation: U=656.00, p=0.0003U = 656.00, p = 0.0003. This is the strongest statistical evidence of a gender difference among the eight items. Male respondents have a higher proportion of strong agreement. The remaining items (F1, S1, T1, SR3 and L1) have p>0.05p > 0.05.

4. Discussion

The results of this study appear to be consistent with an increasing body of research showing that higher education students generally have positive opinions about AI-assisted academic work, but they also want to maintain a clear level of oversight and professional judgement (Zawacki-Richter et al., 2019; Luckin et al., 2016). A readiness cut-off that might aid in the early pilot rollout of AI advising tools is suggested by the fact that all five hypotheses (L1–L5) were validated with composite means over 3.50.

Because preparedness is frequently regarded as a crucial antecedent to technology adoption under the Technology Acceptance Model (Davis, 1989), the top construct means for Student preparedness (L4, M = 3.863) is rather optimistic. Additionally, a more complementary than substitutive view of AI is supported by the strong agreement with FR3 (M = 3.98), which states that AI should enhance student judgement rather than replace it. This makes it compatible with "human-in-the-loop" AI governance strategies, which are being frequently promoted in educational settings (Holmes et al., 2022).

However, it is difficult to overlook the dependability concerns, particularly for L2 (α = 0.093) and L4 (α = 0.458). This is a significant restriction. The nearly 0 alpha in L2 suggests that the three elements might be touching multiple, conceptually distinct concepts rather than just one common idea. The item-total analysis, which shows a negative correlation between S1 (r = −0.084) and the overall construct, supports this as well. A clear indication of construct invalidity is that negative association. In subsequent research,

it would be prudent to isolate S3 (graduation delays) from the Smart Recommendations construct before subjecting the tool to Exploratory Factor Analysis.

When comparing student academic levels, there were no notable changes, but there were clear specialisation effects. This pattern suggests that how AI is viewed in this school is more influenced by discipline culture than by academic seniority. Since AI ready training and sensitisation may need to be created with the particular exposures and expectations of IT, Cyber Network, and Software specialisations in mind, there are also practical ramifications.

5. CONCLUSION

Predictive Suggestions, Functional Reliability, Performance of the Organization, Predictive analytics skills and student preparedness. At the construct level, all five hypotheses were supported ($M \geq 3.50$). But before strong confirmatory causal interpretations can be supported, the reliability results show that the measuring tools still require improvement, particularly for Predictive Recommendations and Student Readiness. For bespoke institutional rollout planning, that provides a very flexible basis. Therefore, the study suggests: (1) beginning pilot deployment of AI advising tools with constructs demonstrating higher reliability (L3 – Administrative Efficiency); (2) updating the instrument using EFA procedures and verifying content validity; (3) conducting longitudinal follow-ups following AI implementation so that attitudinal change can be tracked; and (4) putting in place specialization-specific AI literacy training programs.

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