



Perception of Faculty Towards AI-Assisted Course Advising: An Empirical Investigation at UTAS Al Musanna

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ABSTRACT

This study is looking into how faculty feel about using Artificial Intelligence (AI) for course advising, specifically in the Department of Computing and Information Sciences at the University of Technology and Applied Sciences (UTAS) – Al Musanna, Sultanate of Oman. The data was gathered from 122 respondents, including Diploma, Advanced Diploma, and B.Tech students. These students came from three specializations: Information Technology, Cyber Network, and Software Engineering. To do this, a structured questionnaire with a five-point Likert scale was used, and it aimed at five assumed themes: Functional Accuracy (H1), Smart Recommendations (H2), Administrative Efficiency (H3), Faculty Readiness (H4), and Forecasting Capability (H5). The analysis involved descriptive statistics, Kruskal-Wallis non-parametric tests, and Cronbach's Alpha for reliability checking. Overall, the results point to fairly positive faculty perceptions on all five constructs, and the composite means were within the "Agree" area, roughly $M = 3.50-3.86$. When it comes to differences, the statistical significance showed up mostly with specialization, rather than gender or academic level, so there's that. Reliability came out acceptable only for Administrative Efficiency ($\alpha = 0.779$), while the other constructs were questionable to poor, meaning there is still room to refine the instrument. In the end, the study adds empirical support to the ongoing conversation about integrating AI into higher education advising systems.

KEYWORDS: Artificial Intelligence, Course Advising, Faculty Perception, Higher Education, Kruskal-Wallis, Reliability Analysis, UTAS – Al Musanna.

Introduction

The integration of Artificial Intelligence (AI) into academic advising is kind of a big, transformative shift, in how higher education institutions manage student progression, course selection, and at the same time administrative efficiency. As universities deal with more students than before, and degree requirements that are honestly getting more complicated, AI-powered advising systems feel like they could scale better, stay more consistent, and make decisions based on data instead of just feeling. But of course, whether this actually works depends a lot on what faculty members think, and how ready they feel, since they are the ones interacting with students and the institutional processes every single day.

This empirical study looks at faculty perceptions across five main dimensions: (1) functional accuracy and error reduction, (2) smart course recommendations, (3) administrative and scheduling efficiency, (4) faculty readiness and comfort, and (5) forecasting and demand planning capability. The research is based on information collected from 122 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, non-parametric inferential testing (Kruskal-Wallis H), and reliability checks including internal consistency via Cronbach's Alpha, which are aligned with expectations for publishing in peer-reviewed academic journals.

Artificial Intelligence (AI) has turned into one of the most influential technological innovations that drive digital transformation across many different areas, healthcare, finance, manufacturing, transportation, and education too. In higher education, AI technologies are now being placed into institutional operations more frequently, to raise academic quality, automate the administrative side, increase student engagement, and also help intelligent decision-making systems work better [1], [2]. This increased adoption of AI-driven educational technologies lines up with the broader movement toward smart campuses, data-informed educational ecosystems, and learning environments that are digitally enabled in a more practical way.

Academic advising itself is a key institutional activity that shapes student retention, academic progress, learning outcomes, and graduation rates in a direct way. When advising works well it helps students with choosing courses, planning their progression, getting career guidance, and dealing with academic problems. Still, conventional advising systems often run into issues like very high student-to-advisor ratios, administrative over-load, slow recognition of students who are academically at risk, and manual monitoring that tends to be inefficient [3], [4]. Because of that, the institution becomes less responsive and support services do not hit as effectively as they should. Newer developments in AI, machine learning, educational data mining, and predictive analytics open a chance to handle these gaps through intelligent academic advising systems. AI-assisted advising approaches can process large student datasets, surface risk patterns, predict academic outcomes, and create more personalized suggestions for course selection and progression planning [5]. In that sense, these systems enable earlier intervention, while also letting academic advisors spend more time on the complicated student issues that need human contact and emotional intelligence, not just automation.

On top of that, putting AI into higher education matches broader institutional digital transformation plans and “smart learning” efforts. Universities around the globe increasingly fund intelligent educational technologies, not just for better daily operations but also for competitiveness and evidence-based decision-making [6]. AI-supported systems can also help create personalized learning experiences, automate progression tracking, and build adaptive educational environments, and that tends to raise satisfaction levels and academic performance. Even with these benefits, there are still worries that affect how stakeholders view AI in schools. Trust, transparency, ethical governance, algorithmic bias, privacy, and the level of human oversight remain persistent hurdles that influence adoption [2]. Stakeholders might hesitate to lean entirely on automated tools, especially if they cannot clearly see how the decisions were formed or how student data are being used. This study focuses on stakeholder opinions about AI-assisted academic advisement and student progression systems, using a quantitative research format. More specifically, it looks at connections among trust in AI systems, operational efficiency, workload reduction, ethical concerns, and implementation readiness. The results are expected to support the creation of intelligent academic advising frameworks, and offer evidence-based insights for higher education institutions that are planning how to integrate AI without jumping in blindly, or ignoring the human side.

BACKGROUND OF THE STUDY

Student retention, progression monitoring, and timely graduation are often treated as big performance markers for judging institutional effectiveness in higher education. Universities keep looking for fresher ways to push academic success, lower dropout rates, and strengthen student support mechanisms. In this context, the early identification of academically at-risk students is still really key, because it helps enable timely actions and tends to improve the overall institutional outcomes [7]. However, traditional academic monitoring systems usually depend on manual workflows, and that can lead to delayed intervention, uneven monitoring habits, and plain administrative friction. These issues get worse when enrolment keeps expanding, and when educational systems themselves become more complex. Because of this, higher education institutions need intelligent systems that can handle scalable and proactive student assistance. Not just reactive stuff, but the kind of monitoring that moves before problems fully surface.

AI-assisted advising systems, in particular, offer quite a few possibilities for strengthening academic monitoring and supporting institutional decisions. Using predictive analytics, machine learning models, and intelligent recommendation engines, AI tools can spot learning patterns, estimate academic risks, and propose personalized intervention suggestions [8]. More recent work also suggests that predictive educational analytics can meaningfully enhance student performance forecasting and improve the efficiency of institutional planning [9]. And yes, that means less guesswork, more informed guidance. In practice, AI technologies can support multiple academic functions, such as:

- Student progression tracking

- Academic risk prediction
- Personalized learning routes
- Intelligent course suggestion systems
- Advisement workload management
- Data-driven institutional decision making

At the same time, the increasing adoption of AI in education matches wider digital transformation efforts and the broader idea of smart educational ecosystems [10]. Universities are investing more in AI-driven tools, aiming to boost administrative efficiency, improve learning experiences, and strengthen institutional competitiveness. Yet, ethical concerns—especially around privacy, transparency, data governance, and algorithmic bias—still affect implementation readiness and how stakeholders feel about adoption [11]. So, the rollout of AI-assisted academic advising systems depends not only on technical performance, but also on institutional readiness, user trust, ethical oversight, and solid human-AI collaboration models.

LITERATURE REVIEW

Artificial Intelligence has pretty much turned into one of the most influential technologies that are shaping today's higher education systems, and honestly it feels like that impact keeps growing. AI technologies are being used across adaptive learning environments, intelligent tutoring systems, recommendation systems, educational data mining, and predictive analytics applications [12]. More and more researchers are coming around to the idea that AI is a key driver of educational change and institutional innovation. Russell and Norvig defined AI as systems that can simulate human intelligence through reasoning, learning, and decision-making processes [13]. That early, foundational work sort of laid down the theoretical groundwork for intelligent educational systems and for AI-supported learning settings. In the same way, educational data mining and learning analytics now act as crucial ingredients in predictive academic systems. Baker and Inventado argued that educational analytics allow institutions to spot students who are academically at risk, and then run proactive intervention plans [5]. Likewise, Siemens and Long framed learning analytics as a transformative approach for better educational decision-making, stronger student engagement, and more careful monitoring of academic progress [14].

Arnold and Pistilli developed predictive analytics systems able to flag students who need academic intervention. Their results basically showed that learning analytics tools can improve retention rates, and they can also boost student success outcomes [7]. Those predictive models enable early warning systems, which then help institutions respond faster and more effectively. Chen, Chen, and Lin also pointed out that AI technologies are playing an increasing role in educational transformation, automation, and personalized learning environments [1]. In their view, AI-driven systems raise institutional efficiency while also improving learning experiences and supporting educational quality assurance. Chassignol et al. discussed AI trends in education, and they explained how intelligent technologies feed into adaptive learning, educational automation, and smart learning environments [12]. Overall, their findings back the increasing embedding of AI technologies into education ecosystems. Daniel noted that when AI is implemented in education, it needs ethical governance, accountability, transparency, and responsible human supervision [15]. They also stressed that privacy worries and ethical risks are still some of the biggest roadblocks to AI adoption in schools and universities. Holmes, Bialik, and Fadel argued that AI can improve educational effectiveness by automating repetitive work, and by supporting personalized learning experiences [16]. Their central point was that AI should assist rather than replace educators, and academic advisors too.

Luckin et al. went further and proposed collaborative human-AI educational models that aim to improve institutional effectiveness, while still keeping real human contact meaningful inside academic contexts [17]. This kind of human-AI collaboration seems especially relevant in advising systems, because emotional intelligence and contextual understanding are kind of non-negotiable there. Zawacki-Richter et al. carried out a systematic review of AI applications in higher education, and they concluded that AI is used quite broadly for prediction, assessment, profiling, and intelligent tutoring systems [2]. Their evidence supports the idea that institutions are increasingly depending on AI-enabled educational technologies. On top of that, technology adoption theories also offer helpful lenses for analysing how stakeholders accept AI systems. Davis introduced the Technology Acceptance Model (TAM), with perceived usefulness and perceived ease of use as key determinants of adoption [18]. Similarly, Venkatesh et al. proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), identifying performance expectancy, effort expectancy, and social influence as major adoption drivers [19]. Trust has also shown up as a major factor shaping whether people are willing to accept AI. Kerr and Murthy demonstrated that trust and transparency strongly affect user willingness to adopt intelligent technologies and automated systems [20]. And trust matters even more in academic advising systems, since

insti-tutional decisions can directly shape student outcomes.

Khalil and Ebner explored learning analytics use in MOOCs and showed that predictive analytics models can effectively spot students who are academically struggling [21]. In their results they underlined, the need for analytics-based action plans to help with student retention a lot more smoothly. Bond et al., looked at digital transformation in higher education and pointed out, kind a strongly, that AI literacy along with institutional readiness is becoming essential when tech has to be deployed properly [6]. In a similar direction Garcia-Penalvo et al. examined institutional digital transformation approaches, and argued for AI supported educational structures as a key requirement [22]. Also, research around predictive educational systems has grown noticeably over the last years. Albreiki, Zaki, and Alashwal did a systematic review on machine learning approaches for student performance forecasting, and they found that predictive methods really do help with academic progression analysis as well as with institutional planning [9].

Patel and Goyal studied human AI teamwork inside academic advising systems, and they concluded that AI technologies enhance advisor efficiency while still giving more personalized student support and evidence-based decisions at the institutional level [23].

Ahmed and Al-Mamari focused on AI readiness in higher education institutions across the Gulf region, and they identified a rising level of organizational attention toward intelligent educational technologies and smart campus programs [24]. Their outcomes also further stress how important organizational readiness is, and how digital transformation strategies can make or break implementation. Brown and Wilson investigated the ethical implications that come with AI rollouts in higher education, and they emphasized worries about privacy, algorithmic bias, transparency, and responsible AI governance [11]. These ethical issues still shape stakeholder confidence, and they also affect how ready institutions feel to implement these solutions. Sharma and Sharma, highlighted the function of AI enabled educational systems for supporting smart learning environments, and improving student engagement through intelligent educational ecosystems [25]. Likewise, Wang and Wang demonstrated that AI applications can boost institutional performance, automate student management processes, and enable more personalized educational services [10].

Even with these advances, there are not many studies that specifically examine stakeholder perceptions of AI assisted academic advisement systems within developing educational settings. So, this study contributes by tying together AI adoption theories, educational analytics frameworks, and statistical analysis methods, to assess perceptions related to AI assisted academic advising systems across higher education institutions.

Research Methodology

2.1 SAMPLE AND INSTRUMENT

A cross-sectional survey design was used, sort of a snap shot approach. The study had a sample of N = 122 respondents taken from three academic levels, namely Diploma, Advanced Diploma and B.Tech. These respondents also came from three specializations (IT, Cyber Network, and Software Engineering) within the Department of Computing Information Sciences, UTAS – Al Musanna. For data collection a structured questionnaire of 15 items was applied, where each item used a five-point Likert scale. The anchors were 1 = Strongly Disagree to 5 = Strongly Agree. The questions were arranged into five constructs, and these were aligned with five research hypotheses.

2.2 STATISTICAL METHODS

The data were analysed using several steps. First, frequency analysis was used for a demographic outline. Then descriptive statistics were calculated, including mean, standard deviation, skewness, and kurtosis, mainly for checking each item's pattern. After that, Kruskal-Wallis H non parametric tests were performed to see differences across gender, student level, and specialization, because the Likert data is ordinal in nature, so normal assumptions aren't fully safe. Finally, Cronbach's Alpha was computed to check internal consistency. To support the significance results, effect sizes (η^2) were also estimated. All tests ran at $\alpha = 0.05$.

Results

3.1 DEMOGRAPHIC PROFILE OF RESPONDENTS

Table I presents the demographic characteristics of the 122 respondents. The sample was predominantly female (80.3%, n = 98) with male respondents constituting 19.7% (n = 24). By academic level, Diploma

students formed the largest group (50.0%, n = 61), followed by B.Tech (31.1%, n = 38) and Advanced Diploma (18.9%, n = 23). In terms of specialization, IT students were the majority (67.2%, n = 82), followed by Cyber Network (19.7%, n = 24) and Software (13.1%, n = 16).

Table I Demographic Profile of Respondents (N = 122)

Variable	Category	n	%	Cumulative %
Gender	Male	24	19.7	19.7
	Female	98	80.3	100.0
Student Level	Diploma	61	50.0	50.0
	Advanced Diploma	23	18.9	68.9
	B.Tech	38	31.1	100.0
Specialization	Information Technology	82	67.2	67.2
	Cyber Network	24	19.7	86.9
	Software	16	13.1	100.0

Note. Values represent frequency counts (n) and valid percentages (%). Total N = 122.

The sample composition kind of indicates a strong female majority (80.3%), it reflects the gender distribution, that is typical for social science and business programmes at UTAS. You can also see that Diploma-level re-spondents dominate (50.0%), and that helps ensure representation from the early, foundational programme years. On top of that, the IT specialization presence, it comes out high (67.2%) and that matches the usual institutional enrolment patterns. These demographic traits sort of need to be taken into account when inter-preting specialization-based differences, in the next analyses that follow.

3.2 DESCRIPTIVE STATISTICS

Table II presents item-level descriptive statistics for all fifteen scale items across the five hypothetical constructs. Means are interpreted using the following scale: 1.00–1.49 = Strongly Disagree; 1.50–2.49 = Disagree; 2.50–3.49

= Neutral; 3.50–4.49 = Agree; 4.50–5.00 = Strongly Agree.

Table II Descriptive Statistics for All Scale Items (N = 122)

Item	Statement	N	Mean	SD	Min	Max	Skew	Interp.
H1 – Functional Accuracy								
F1	AI would re-duce human er-ror in course ad-vising	122	3.73	0.962	1	5	- 0.779	Agree
F2	AI can im-prove con-sistency and ac-curacy of advis-ing decisions	122	3.84	0.930	2	5	- 0.165	Agree
F3	AI can im-prove student academic pro-gression	122	3.98	0.692	3	5	0.021	Agree
H2 – Smart Recommendations								

S1	AI can analyze student data to recommend next-semester courses	122	3.79	1.046	1	5	- 1.131	Agree
S2	AI-generated recommendations will benefit students	122	3.85	0.924	1	5	- 0.714	Agree
S3	AI can reduce delays in graduation	122	3.48	0.911	1	5	- 0.618	Neutral
H3 – Administrative Efficiency								

T1	AI can flag students who do not meet prereq-uisites or CGPA conditions	122	3.57	1.171	1	5	- 0.716	Agree
T2	AI will reduce time spent re-viewing student records	122	3.84	1.071	1	5	- 0.968	Agree
T3	AI will streamline course offering and scheduling preparation	122	3.74	0.736	3	5	0.454	Agree
H4 – Faculty Readiness								
FR1	I feel comfort-able using AI-as-sisted advising tools	122	3.79	0.855	1	5	- 0.535	Agree
FR2	I would verify AI recommenda-tions before ap-proving them	122	3.83	1.002	1	5	- 0.642	Agree
FR3	AI can sup-port—but not re-place—teacher judgment	122	3.98	1.167	1	5	- 1.079	Agree
H5 – Forecasting Capability								
H1	AI can predic course demand and section re-quirements ac-curately	122	3.31	0.997	1	5	- 0.302	Neutral
H2	Forecasting course demand is challenging with current methods	122	3.72	0.893	1	5	- 0.543	Agree
H3	AI can auto-generate projec-tion sheets for programs	122	3.47	1.173	1	5	- 0.600	Neutral

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 = Neutra.

Of the fifteen items, fourteen were kind of rated in the “Agree” band ($M \geq 3.50$), which means faculty opinions about AI in advising were mostly positive. The top pick, F3 ($M = 3.98$, $SD = 0.692$), seemed to get the clearest support, basically pointing toward a strong agreement that AI can help academic progression

and it also had a distribution that looks almost balanced, Skewness = 0.021. Another one that also landed high was FR3 (M = 3.98, SD = 1.167), where respondents still leaned to the idea that AI should add to rather than substitute faculty judgment. Even so, that larger SD suggests people were more spread out in how they answered, not as uni-form.

Then, two items showed up around the “Neutral” zone: S3, about AI reducing graduation delays (M = 3.48), and H1, about AI predicting course demand (M = 3.31). Those scores kinda reflect more hesitation for those particular uses. Also, the negative skewness you see across most items suggests a general tendency toward agreement, which matches the overall positive pattern. F3 again looks like the tightest cluster in terms of con-sensus since it had the narrow range (Min = 3, Max = 5, SD = 0.692). By contrast, T1 (SD = 1.171) and H3 (SD = 1.173) show the widest divergence, so opinions there weren’t as aligned, or at least not in the same way.

3.3 HYPOTHESIS CONSTRUCT SUMMARY

Table 3 presents composite descriptive statistics at the construct level, aggregating responses across the three items constituting each hypothesis. This provides an overall assessment of each hypothetical dimension.

Table III Hypothesis Construct-Level Descriptive Statistics (N = 122)

Hyp.	Construct	Mean	SD	Min	Max	Var-iance	Sup-port
H1	Functional Accuracy (F1, F2, F3)	3.850	0.658	2.33	5.00	0.434	Sup-ported ✓
H2	Smart Recommendations (S1, S2, S3)	3.705	0.574	2.33	5.00	0.329	Sup-ported ✓
H3	Administrative Efficiency (T1, T2, T3)	3.713	0.841	1.67	5.00	0.708	Sup-ported ✓
H4	Faculty Readiness (FR1, FR2, FR3)	3.863	0.704	2.67	5.00	0.495	Sup-ported ✓
H5	Forecasting Capability (H1, H2, H3)	3.500	0.780	2.33	5.00	0.608	Sup-ported ✓

Note. Hypotheses supported where composite M ≥ 3.50 (Agree range). SD = Standard Deviation. All con-structs are based on three items each.

All five hypotheses were empirically supported, with composite means ranging from 3.500 (H5 – Forecasting Capability) to 3.863 (H4 – Faculty Readiness). Faculty 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 (H1) ranked second (M = 3.850), reflecting confidence in AI's capacity to reduce error and improve consistency. Administrative Efficiency (H3) 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 (H5), 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 $\alpha \geq 0.70$ (Nunnally, 1978), though values ≥ 0.60 are considered acceptable in exploratory studies.

Table IV Reliability Statistics – Cronbach's Alpha per Construct

Hyp.	Construct	N Items	N Cases	Cronbach's α	Interpretation
H1	Functional Accuracy	3	122	0.627	Questionable
H2	Smart Recommendations	3	122	0.093	Unacceptable
H3	Administrative Efficiency	3	122	0.779	Acceptable
H4	Faculty Readiness	3	122	0.458	Unacceptable
H5	Forecasting Capability	3	122	0.633	Questionable

Note. Interpretation thresholds: $\alpha \geq 0.90$ = 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 H3 – Administrative Efficiency met the acceptable reliability threshold ($\alpha = 0.779$), kinda approaching the usual 0.80 benchmark. H1 ($\alpha = 0.627$) and H5 ($\alpha = 0.633$) sit in that “questionable” area, so the results should be read with care. Most importantly, H2 – Smart Recommendations ($\alpha = 0.093$) 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, H4 – Faculty Readiness ($\alpha = 0.458$) drops under the acceptable level, meaning FR1 FR2 and FR3 are kinda 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)

Hyp.	Item	Item Description	Scale Mean if Deleted	Scale Var. if Deleted	Cor-rected Item-Total r	α if Item Deleted
H1	F1	AI reduces human error in advising	7.820	1.736	0.489	0.451
	F2	AI improves consistency & accuracy	7.713	1.876	0.456	0.502
	F3	AI improves student academic progression	7.566	2.562	0.389	0.601
H2	S1	AI recommends next-semester courses	7.328	2.123	-0.084	0.414
	S2	AI recommendations benefit students	7.262	1.699	0.170	-0.265
	S3	AI reduces graduation delays	7.639	1.918	0.085	-0.032
H3	T1	AI flags prerequisite/CGPA issues	7.574	2.759	0.575	0.776
	T2	AI reduces time reviewing records	7.303	2.759	0.693	0.612
	T3	AI streamlines course scheduling	7.402	3.912	0.657	0.713
H4	FR1	Comfort using AI-assisted tools	7.803	2.820	0.316	0.322

	FR2	Would verify AI recommendations	7.762	2.563	0.278	0.366
	FR3	AI supports but not replaces judgment	7.615	2.173	0.268	0.404
H5	H1	AI predicts course demand accurately	7.189	2.815	0.498	0.457
	H2	Forecasting is challenging currently	6.779	3.562	0.331	0.671
	H3	AI auto-generates projection sheets	7.033	2.263	0.521	0.418

Note. Corrected Item-Total r values below 0.30 indicate weak item-construct correlation. Negative α -if-deleted values (H2: S2, S3) confirm construct invalidity. Red cells = problematic values; Green cells = strong values.

3.5 INFERENTIAL ANALYSIS – KRUSKAL-WALLIS H TESTS

Non-parametric Kruskal-Wallis H tests were conducted to examine whether statistically significant differences existed in item responses across three demographic grouping variables: Gender (Male, Female), Student Level (Diploma, Advanced Diploma, B.Tech), and Specialization (IT, Cyber Network, Software). The Kruskal-Wallis test was selected as the appropriate alternative to one-way ANOVA given the ordinal nature of Likert-scale data. Effect sizes were computed as $\eta^2 = (H - df) / (N - df - 1)$. Table 6 summarises all significant results ($p < .05$).

Table VI Summary of Significant Kruskal-Wallis H Test Results ($p < .05$)

Item	Statement	Grouping Variable	H	df	p	η^2	Effect
F1	AI reduces human error in advising	Gender	4.906	1	.027*	0.033	Small
F3	AI improves student academic progression	Gender	6.202	1	.013*	0.043	Small
F3	AI improves student academic progression	Specialization	19.625	2	<.001***	0.148	Large
S1	AI recommends next-semester courses	Specialization	17.137	2	<.001***	0.127	Medium
S3	AI reduces graduation delays	Gender	4.060	1	.044*	0.026	Small
S3	AI reduces graduation delays	Specialization	8.910	2	.012*	0.058	Small
T1	AI flags prerequisite/CGPA issues	Specialization	9.194	2	.010*	0.061	Medium
FR2	Would verify AI recommendations	Gender	14.731	1	<.001***	0.114	Medium
FR2	Would verify AI recommendations	Specialization	18.546	2	<.001***	0.139	Large

FR3	AI supports but not replaces judgment	Specialization	17.080	2	<.001***	0.127	Medium
H1	AI predicts course demand accurately	Specialization	7.810	2	.020*	0.049	Small
H2	Forecasting is challenging currently	Specialization	10.449	2	.005**	0.071	Medium
H3	AI auto-generates projection sheets	Specialization	7.267	2	.026*	0.044	Small

Note. Only statistically significant results ($p < .05$) are displayed. *** $p < .001$; ** $p < .01$; * $p < .05$. Effect size: $\eta^2 \geq 0.14$ = large; ≥ 0.06 = medium; ≥ 0.01 = small. Non-significant results (all Student Level comparisons and most Gender comparisons) are omitted for brevity.

So, the inferential analysis comes back with basically three key observations, like, kinda in a clear way. First, specialization turned out to be the most consistent reason for significant group differences, and it actually produced significant results on all five constructs (H1–H5). Meanwhile student academic level showed no significant differences on any item, so it feels like perceptions of AI in advising are pretty much the same across Diploma, Advanced Diploma, and B.Tech levels. Second, gender differences did show up, but only on three items F1 ($H = 4.906$, $p = .027$), F3 ($H = 6.202$, $p = .013$), and FR2 ($H = 14.731$, $p < .001$), with effect sizes that sit from small ($\eta^2 = 0.033$ – 0.043) up to medium ($\eta^2 = 0.114$). The medium effect for FR2 is especially worth pausing on, because it implies that male and female respondents really do differ, meaningfully, in their intention to check AI recommendations before they approve them, basically. Third, the most prominent effect over-all shows for F3, but only by specialization ($\eta^2 = 0.148$, $p < .001$), which is large, and suggests that Software, Cyber Network, and IT students basically do not see AI's ability to enhance academic progression in the same way — and that F3 was also the highest rated item in the whole study. Also, FR2 by Specialization came out with a close-to-large pattern ($\eta^2 = 0.139$, $p < .001$), again $p < .001$. Overall, these findings point to AI adoption strategies that should be tailored by specialization, and they also hint that gender-sensitive messaging might be useful, particularly for the verification related features.

Discussion

The findings of this study seem to sit with a growing strand of literature pointing out that faculty in higher education usually hold generally favourable views about AI assisted academic work, but at the same time they want to keep a clear level of oversight and professional judgement (Zawacki-Richter et al., 2019; Luckin et al., 2016). The fact that all five hypotheses (H1–H5) were supported, with composite means above 3.50 suggests a kind of readiness cut-off that could help the early pilot roll out of AI advising tools.

The top construct mean shows up for Faculty Readiness (H4, $M = 3.863$), which is pretty encouraging, because readiness is often seen as a key antecedent to technology adoption within the Technology Acceptance Model (Davis, 1989). Also, the strong agreement for FR3 ($M = 3.98$) — AI should support but not replace faculty judgement — fits a more complementary than substitutive view of AI. In that sense it links well with “human-in-the-loop” AI governance approaches that are now commonly argued for in learning environments (Holmes et al., 2022).

Still, the reliability worries are hard to ignore, mainly for H2 ($\alpha = 0.093$) and H4 ($\alpha = 0.458$). This counts as a serious limitation. The almost zero alpha in H2 hints that the three items may be tapping not one shared idea but several, conceptually different things. This is also backed by the item-total analysis, where S1 ($r = -0.084$) is negatively associated with the overall construct. That negative relationship is a rather direct sign of construct invalidity. For future work, it would be wise to separate S3 (graduation delays) away from the Smart Recommendations construct, then run the instrument through Exploratory Factor Analysis (EFA) or Confirmatory Factor Analysis (CFA) before any inferential testing is attempted.

When we look at differences, there were no significant gaps across student academic level, but strong specialization effects were evident. This pattern points to disciplinary culture, more than academic seniority, as the driver for how AI is perceived in this institution. There are practical consequences here too, since AI readiness

training and sensitisation may need to be designed with the specific exposures and expectations of IT, Cyber Network, and Software specializations in mind.

Conclusion

Overall, this study gives empirical support that faculty at UTAS – Al Musanna has positive perceptions of AI in course advising across five dimensions: functional accuracy, smart recommendations, administrative efficiency, faculty readiness, and forecasting capability. All five hypotheses were supported at the construct level ($M \geq 3.50$). However, the reliability results indicate that the measurement instruments still need refinement, especially for Smart Recommendations and Faculty Readiness, before strong confirmatory causal interpretations can be justified.

A major point is that specialization seems to matter more than gender, or academic level, as a differentiator of AI perceptions. That offers a rather flexible baseline for customised institutional rollout planning. The study therefore recommends: (1) starting pilot deployment of AI advising tools with constructs showing higher reliability (H3 – Administrative Efficiency); (2) revising the instrument using EFA procedures and checking content validity; (3) running longitudinal follow ups after AI implementation, so attitudinal change can be monitored; and (4) implementing specialization-specific AI literacy training programmes.

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