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Understanding Student Perceptions of AI Tools in Higher Education: Evidence from UTAS Salalah

Dr. Nasser Mohammed Alhamar Alkathiri[1], Dr. Ravishankar Krishnan[2*], Dr. Navaneetha Krishnan Rajagopal[3], Dr. Sanyo Moosa[4] and Dr. Shelly Mohanty[5]

[1]Dean, College of Economics & Business Administration, University of Technology and Applied Sciences, Salalah, Sultanate of Oman
[2*]Professor, School of Management, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India
[3]Faculty, College of Economics & Business Administration, University of Technology and Applied Sciences, Salalah, Sultanate of Oman
[4]Faculty, College of Economics & Business Administration, University of Technology and Applied Sciences, Salalah, Sultanate of Oman
[5]Faculty, College of Economics & Business Administration, University of Technology and Applied Sciences, Salalah, Sultanate of Oman
E-mail: [1]nasser.m.alkatheri@utas.edu.om, [2]ravimba20082@gmail.com, [3]navaneetha.rajagopal@utas.edu.om, [4]sanyo@utas.edu.om, [5]shelly.mohanty@utas.edu.om
ORCID: [1]https://orcid.org/0000-0001-9494-7366, [2]https://orcid.org/0009-0004-6609-6452, [3]https://orcid.org/0009-0004-4476-3867, [4]https://orcid.org/0000-0002-0413-7448, [5]https://orcid.org/0009-0007-6304-347X

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Abstract - **This study intends to explore student perception towards the implementation of Artificial Intelligence (AI) tools in the context of higher education with specific reference to the University of Technology and Applied Sciences (UTAS) - Salalah in Oman. Although AI integration in education is accelerating globally, empirical evidence on how students perceive AI tools vis-à-vis their satisfaction, usage benefit, and perceived benefits, especially within the Oman higher education context, remains scarce. To address this gap, this study investigates the effect of system quality, information quality, and service quality on user satisfaction, use benefit, and perceived net benefits, applying the DeLone and McLean Information Systems (IS) Success Model. A structured questionnaire was administered to 133 university students as part of a quantitative research approach. After that, the data was examined using Partial Least Squares-Structural Equation Modeling (PLS-SEM), which employed a two-stage approach to assess the structural and measurement models. Other validation of the model was performed using Q²_predict and model fit validation. The study found that the information and service quality significantly affect both user satisfaction and use benefit, which also have a net positive impact. The system, however, did not show a statistically meaningful effect on either use benefit or user satisfaction with the system's quality. This research provides the first application of the IS Success Model related to the adoption of generative AI in the context of higher education within Oman's Vision 2040 blueprint for digital transformation.**

Keywords: **Artificial Intelligence (AI) In Education, Information Systems (IS) Success Model, Higher Education, Student Satisfaction, Oman Vision 2040**

I. INTRODUCTION

Artificial Intelligence (AI) has transformed from a futuristic idea to a present-day utility that is a part of our everyday life. Significant advancement has occurred in machine learning and natural language processing, which in turn has brought to the fore very practical AI applications in a number of sectors like health care, finance, logistics, and also education (Mehrabian & Russell, 1974). Among various sectors, the field of education has notably experienced the rise of generative AI tools that are able to produce human-like text, images, and analysis, fundamentally transforming the teaching and learning environments (Maurya et al., 2023; Hajipour, 2014).

These tools are providing students with real-time content creation, task automation, and adaptive feedback, which in great measure is changing how the educational community accesses and processes information. AI technologies are now more than ever integrated into digital learning systems, aiming to improve the academic performance and engagement of students (Zawacki-Richter et al., 2019). In the education context, Oman is not an exception, and students can use these systems for content summarization, paraphrasing, sectioning, and being able to comprehend texts better, thus lessening the mental burden placed on them while maximizing productivity. As dependence on AI continues to grow, it is essential to pay attention to how students interact with and use these technologies in terms of their value, satisfaction, usability, and academic benefit (Almufarreh, 2024). Also, in the case of Oman Vision 2040, the focus is on the integration of technology in education as part of the national development plan (Bhandari & Mohite, 2024). Oman Vision 2040 focuses on the integration of technology in education as part of the national development strategy (Al-Alawi & Jawarneh, 2023). Oman's higher education universities, particularly the University of Technology and Applied Sciences (UTAS) – Salalah, AI AI-powered solutions to encompass broader strategic educational goals. The objective of these initiatives goes beyond enhancing the educational framework to include training learners on skills in a digital economy. Despite increasing integration of AI, there is limited empirical evidence on the extent to which policy initiatives, combined with student use of AI technologies to suggest that AI driven systems will be perceived as beneficial by students in Oman (Syahrin & Akmal, 2024; Seddon & Yip, 1992).

To fill this gap, the present study, based on the (DeLone & McLean, 2003) success model for information systems (IS), brings together the key elements of system quality, information quality, User benefit, satisfaction, and net benefits to report on the performance of artificial intelligence tools in higher education. The IS Success Model is a proven tool in tech adoption research and does an excellent job of looking at the performance and impact of digital systems from the user perspective (Petter et al., 2008). From this base, the study explores how the quality of AI systems (System Quality), the accuracy and relevance of AI-generated content (Information Quality), and the access to support (Service Quality) play a role in determining User Satisfaction and Perceived Net Benefits. Further, the analysis examines how these factors ultimately contribute to the Net Benefits, namely, the large-scale educational value observed in the adoption of AI tools.

The present research employed an analysis to examine these issues and validated the model using Partial Least Squares-Structural Equation Modeling (PLS-SEM), while also assessing the model's reliability. The investigation had a group of 133 university students who are active users of generative AI tools, and they were our sample, which we put to use for the stats and machine learning based analysis (Barhoumi et al., 2024).

This paper sets out to achieve practical and theoretical contributions. From a theoretical perspective, the research is still emerging, so it roots the application of the IS Success Model with generative AI in higher education. It offers information for educators, system developers, and policy makers on AI and student-centered pedagogical outcomes on learning tools for students (Thaseen & Banu, 2025). By exploring the interrelationships among system quality, content material effectiveness, service experience, satisfaction, and academic benefits, this study aims to deepen our understanding of what drives powerful AI adoption in better education settings—specially in alignment with Oman's country-wide educational goals.

II. Review of Literature

2.1 System Quality

System Quality refers to the degree to which a system performs its intended function very well, very consistently, and very efficiently. In the case of AI tools in education, System Quality includes aspects like interface ease of use, response speed, technical accuracy, uptime reliability, and ease of access (DeLone & McLean, 2003b). These elements play a role in how students perceive the AI platform's design, dependability, and support of academic tasks. A system that has frequent outages, slow response times, or is full of issues is going to frustrate users, who may not use it at all, even if the material it produces is of great value. In AI-based academic settings, System Quality is the basis on which we seek to build trust in the system, support task completion, and, in turn, improve the learning experience.

In the field of educational AI at large and in higher education institutions like the University of Technology and Applied Sciences in Salalah in particular, students are growing to depend on AI tools which they use for summarizing content, completing assignments, and exam prep. For these to be received as useful, they must be of high-tech quality. The present research looks at System Quality to include the stability of the platform, the variety of prompts the system does well with, and its ability to adapt to academic settings. The findings indicate that high performance AI systems not only facilitate smooth interaction but also enable students to put more into their content study rather than into tech issues. Research assessing System Quality in relation to generative AI tools among Gulf students is lacking, despite the IS Success Model's established status. By conducting an empirical test of the relationship between System Quality and two important outcome variables—User Benefits and User Satisfaction—the current study seeks to close this gap.

H1: System Quality positively influences User Benefits.

H2: System Quality positively influences User Satisfaction.

2.2. Information Quality

Information Quality refers to the degree to which information put out by a system is relevant, accurate, complete, timely, and well-presented. In the case of AI tools used in higher education, this term reflects students' perceptions of whether the material put out by these tools supports their academic goals in a meaningful and relevant way to them (DeLone & McLean, 2003a). Also, students expect AI to put out material that is coherent, logistically organized, and tailored to academic settings, especially when used for text summarization, assignment structure, or support in exam preparation.

The educational interactions within Oman, such as at UTAS-Salalah, have students using AI for more sophisticated academic tasks. Some of these tasks include automating communication, analytical tasks, and material preparation. Accomplishing these tasks requires the content to be technically correct and academically sound, devoid of hallucinated, plagiarized, or erroneous information. In this situation, Information Quality integrates depth of content, logical coherence, and alignment with the teaching goals. If information quality is high, students will have confidence in the system, use it often, and achieve better learning results.

Existing literature highlights the significance of Information Quality in digital learning settings. (Al-Fraihat et al., 2020) demonstrated that the clarity and pertinence of information are strong predictors of user satisfaction in e-learning platforms (Balaji et al., 2022; Poroohan & Reshadatjoo, 2019). Equally, (Basri, 2024) noted that content that is specific, complete, and relevant bolsters learning effectiveness and contributes to the value placed on technology-integrated teaching. All this is pertinent as AI instruments are progressively used as active academic collaborators instead of inactive storehouses of information.

In the scope of Oman's Vision 2040, which is to see large-scale digital transformation in the educational sector, we are not only looking at access to AI tools but also the quality of what is put out by those tools. That said, we still do not have many empirical studies looking at Information Quality in the issue of generative AI use among students in Oman or the region at large. This study presents that gap in research by looking at how students perceive the use of AI-generated content in terms of its' value and reliability, and in what ways do those perceptions play a role in the students' overall satisfaction and benefit from that use. Based on the theoretical and empirical insights, the following hypotheses are proposed:

H3: Information Quality positively influences User Benefits.

H4: Information Quality positively influences User Satisfaction.

2.3 Service Quality

Service Quality is what we look at in terms of the support given to users pre, during, and post interaction with a system. In the IS Success Model, this includes things like response time, dependability, technical support, help feature accessibility, and the presence of tutorials or user guides (DeLone & McLean, 2003a). In academic settings for AI tools, this is also related to how the support infrastructure meets the users' needs - whether that is from live tech support, user interface tours, FAQs, or updates that improve the tool's performance over time.

In the area of educational AI services, the quality of service is of great importance. At institutions like UTAS–Salalah that have adopted these technologies, students are observed using them to summarize content, write assignments, or review academic material. The challenges they encounter range from interface issues and poor content generation to access problems. Also, we see that if support resources, which may include tech support, in-product guidance, or video tutorials, are not present or are in fact not of use, students may stop using the tool. But on the other hand, a highly supported AI tool may have the opposite effect, building student confidence, increasing their use of the tool over time, and improving overall satisfaction, thereby making the tool a more usable system.

Several of our empirical studies report on the issue of Service Quality in ed tech. For example, (Almarashdeh 2016) reports which elements of service support are reported by students as most important in their use of learning management systems. Also, (Hamzaoui et al., 2024) report that what they term a responsive support system is what students value in tech-enhanced or hybrid learning settings. The work of (Ozkan & Koseler, 2009) highlights that system support is a great determinant of a student's willingness to look at and use in detail the advanced features of a system. This, in turn, suggests a very strong connection between the quality-of-service infrastructure provided and in turn, the manner in which users engage with the system.

In the Omani setting, in particular as reflected in Vision 2040's digital transformation strategy, which is very much a focus for educational institutions, there is a push for reliable digital infrastructure and user-centered tech services. While significant emphasis has been placed on the adoption of AI tools, the supporting systems that enable this adoption remain largely under-researched. Also, a gap in the research that looks at the role of service quality in the use of AI in higher education in Oman and the Gulf in general (Chavan & Mhatre, 2025). Therefore, this study positions Service Quality as a key element for investigation, proposing that it plays a critical role in influencing student satisfaction and the outcomes derived from the use of AI tools in an academic setting.

H5: Service Quality positively influences User Benefits.

H6: Service Quality positively influences User Satisfaction.

2.4. User Benefits

User Benefits focus on the outcomes and value that a user achieves from interacting with technology. In the IS Success Model, Net Benefits is defined as one of the critical constructs of a system's value to its users and performance, efficiency, satisfaction, and goal attainment (DeLone & McLean, 2003a). In educational settings, User Benefits pertain to the ways in which AI instruments improve students' learning, productivity, knowledge, and overall academic achievement. In post-adoption circumstances, continuous interaction with technology often depends on the user's perception of value, which includes academic performance, learning, and time (Bhattacherjee, 2001). At UTAS–Salalah, where AI tools are progressively embedded within practices of classrooms, User Benefits depicts students' enhancements in coursework, assignments, examinations, and understanding of concepts.

Learners using AI for summarization, content creation, paraphrasing, or problem-solving perceive drastic improvement from the advanced methods – learning efficiency and academic performance value compared to traditional techniques. Studies conducted in e-learning and technology adoption have stressed this relationship between system utilization and benefits obtained. (Kadhim & Hassan 2020) stated that students who appreciate additional benefits provided by e-learning systems demonstrate higher satisfaction levels and better academic achievement. Similarly, (Hu, 2024) noted that the educational value of teaching resources affects the continued use of these tools by students. In Oman, where higher education institutions are proceeding with digital transformation as per Vision 2040, identifying the benefits brought by AI tools becomes crucial. The research aims to fill this gap by exploring how students perceive the contribution of AI tools toward their prospective academic goals and educational value. It is therefore expected that the benefits to users will positively contribute to the academic satisfaction and perceived success of students.

H7: Use Benefit positively influences Net Benefits.

2.5. User Satisfaction

User Satisfaction is a core construct in the DeLone and McLean Information System (IS) Success Model; as such, it is one of the most valuable determinants of how effectively a system operates in meeting user expectations. It captures a user's experience, including all emotions and thought processes, after interacting with an information system (DeLone & McLean, 2003a). In technology adoption literature, satisfaction is an outcome resulting from perceived system efficiency, the quality of content, system usability, and user assistance. It portrays the extent to which a system has achieved an intended goal.

Also, it is put forth that this model is related to Expectation-Confirmation Theory (ECT), which puts forth that satisfaction is achieved when users see that the system has met or exceeded their expectations (Alshammari & Alshammari, 2024). Students are using AI-based platforms more and more in higher education, especially at UTAS–Salalah, to enhance learning, create content, get ready for tests, and produce better assignments. The degree of system dependability, the accuracy and coherence of the content produced, the responsiveness of support mechanisms, and the tool's ability to lessen academic workload are some of the experiential factors that determine how satisfied students are with these tools. A high degree of satisfaction encourages continued use, greater integration into the student's academic routine, and increased trust in the system (Syahrin & Akmal, 2024).

Student satisfaction is a crucial indicator for assessing the efficacy and scalability of AI-based academic interventions in Oman, where higher education is undergoing a substantial technological transformation as part of Vision 2040. Few studies have examined how satisfaction arises specifically in the context of students using AI tools, despite the policy emphasis. Thus, User Satisfaction is a crucial outcome construct in this study, and the following hypothesis is put forth.

H8: User Satisfaction positively influences Net Benefits.

The suggested research framework in Fig. 1 and the postulated correlations between the study variables are depicted in the following figure.

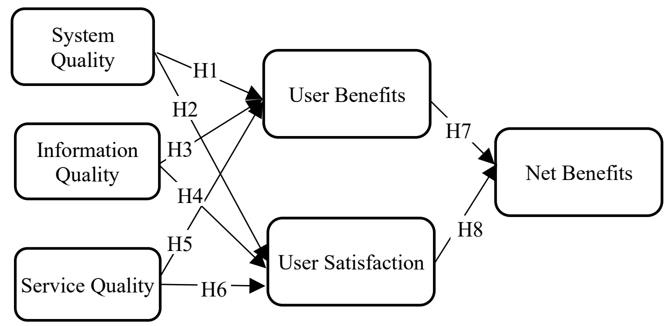

Fig. 1 Conceptual framework

III. METHODOLOGY

3.1 Study Location Justification

Oman was chosen as our study setting, which has been seeing an increase in its higher education reform and digital transformation as per the Oman Vision 2040. This vision puts forth education, research, and innovation as one of the four base pillars for sustainable development, which in turn calls for the integration of advanced technologies like Artificial Intelligence into the teaching and learning settings (Al-Alawi & Jawarneh, 2023). Also, over the past two decades, the country has seen great expansion in its higher education infrastructure, which now includes many higher education institutions that are serving a growing student body (Oman 2040, 2020). The Gross Enrolment Ratio in tertiary education has been on a steady rise, reflecting a widescale national effort to improve access and quality in higher education. Also, in this regards Oman's Digital Education Strategy 2020 it puts forth the introduction of smart technologies in public universities and the development of digital literacy among students and staff (Oman 2040, 2020). In this setting, the University of Technology and Applied Sciences (UTAS) Salalah campus stands out as a leader in applied learning and technology-enhanced education. UTAS has reported having implemented AI-enabled platforms, digital content tools, and blended learning systems in response to national policy and post-pandemic adaptation. Also reported is that its student body is very digital and diverse, which in turn makes the UTAS Salalah an ideal setting in which to study the issues of AI tool adoption and user satisfaction in higher education.

3.2. Population and Sampling

This study considered a population frame comprising all undergraduate and postgraduate students currently enrolled at UTAS in Salalah. These students are from a tech-savvy generation that is increasing its use of AI in the classroom. There are two reasons for choosing students from UTAS–Salalah. First, it is one of the largest and most modern public universities in the southern part of Oman. It has a major digital teaching and learning infrastructure. Secondly, they are at the forefront of using AI in classrooms; thus, their feedback is important to capture real academic use cases. On the other hand, numerous empirical studies have been conducted on the use of AI and AI satisfaction in the educational system in the USA, China, and Malaysia, but there is a striking absence of extensive context research in the GCC countries, particularly Oman. This lack of study is critical because the educational systems of the GCC are structurally and culturally different from those of Western and Far Eastern countries. Therefore, Oman is an overlooked example for fostering policy frameworks, educational resource planning, and technology development integration systems.

So that they could gather the required information, the researchers applied a non-probability purposive sampling method. This is commonly used in exploratory studies and is appropriate when trying to hone in on a particular subgroup within a larger pool, like students who interacted with AI tools for educational purposes. In this case, there is no random selection, as there is in probability samples; the researcher picks the subjects to include in the study based on defined standards set by him/her. Here, the relevant standard was that the participant in question must have come into contact with AI tools like content-generating AI, summarizing AI tools, and chatbot assistants for educational work.

To ensure data validity, filter questions were embedded in the questionnaire. The survey enquired about which specific AI tools our respondents used, the frequency of that use, and for what academic purposes (e.g., exam preparation, writing, concept explanation). Only students who reported actual use were included in the final data set. A mix of online platforms was used to distribute the questionnaire (e.g., email, WhatsApp groups, Google Forms) and also limited offline circulation within UTAS classrooms and common areas over a two-week period. Out of a pool of over 200 students we approached, the study retained 133, which were valid and completely filled out for analysis, which became our final study sample.

Although the sample size may be considered small, it is methodologically sound. Partial Least Squares Structural Equation Modeling is widely recognized as an appropriate methodological approach for studies characterized by small sample sizes as well as those emphasizing predictive analysis or theoretical model development (Sarstedt et al., 2021a). According to the "10 for 1" rule, the sample size should be at least 10 times the maximum number of convergent paths associated with a given latent variable, and this requirement is met in the present study (Sarstedt et al., 2021b). Additionally, (Kock & Hadaya, 2018) report that PLS-SEM can yield valid and reliable results even with fewer than 200 responses in moderately complex models. Thus, the sample size of 133 responses is sufficient and provides a representative context for the analysis conducted.

3.3 Data Collection Instrument

The present study used a structured survey questionnaire as the primary tool for data collection. Respondents were asked to rate each item in the questionnaire using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) (Boone Jr & Boone, 2012). A five-point Likert scale, which is very much the norm in quantitative research, especially in the field of educational technology, for its' proven reliability in the measurement of attitude, perception, and behavior in an easy-to-use format was employed (Joshi et al., 2015).

This study used items adapted from other validated studies, for this research, which in turn covered the issues at hand and also ensured content validity. The questionnaire was developed in both English and Arabic to improve on clarity, cultural relevance, and to better convey the issues relevant to the University of Technology and Applied Sciences (UTAS) in Salalah. Table I presents the variables used in the study, the number of items per variable, and the source of these adapted items.

TABLE I DATA COLLECTION INSTRUMENT

Variable	No. of Items	Source
System Quality	3	(DeLone & McLean, 2003)
Information Quality	3	(DeLone & McLean, 2003)
Service Quality	3	(Parasuraman et al., 1988)
User Benefit	3	(Petter et al., 2008)
User Satisfaction	3	(Bhattacherjee, 2001; Seddon & Yip, 1992)
Net Benefit	3	(DeLone & McLean, 2003c; Petter et al., 2008)

3.4 Socio-demographic Analysis

All survey respondents (n=133) were attending institutions of higher learning in Oman, and were actively enrolled in academic programs at the time of the data collection. The socio-demographic makeup of the sample is quite relevant to the respondents' use of AI systems and their experiences, as it illustrates the rich diversity of the respondents. There was almost equal representation of both sexes, with female participants making up 50.4% and male participants 49.6%. Regarding age, the respondents mostly belonged to the categories of 18-20 years (48.1%) and above 20 years (48.9%), which grossly constitutes university-age learners.

In terms of academic levels grouped as categories, the most considerable chunks of students were first-year (27.1%) and second-year (27.8%) diploma students. Participants were also enrolled in advanced diploma (9.8%) and bachelor's programs (12.8%) to a lesser extent. This suggests that most of the sample participants are at the beginning or moderately advanced stages of their education. In terms of academic fields, the biggest proportion was from Engineering disciplines (48.1%) followed by Business Studies (35.3%) and Arts (16.5%), which implies that the respondents had a higher-than-average engagement in technical and business studies—this is particularly relevant because these students are more likely to engage with AI-enhanced resources within their courses. The goal of evaluating the use of AI tools in a top public university in Oman is well-aligned with the fact that a noteworthy 93.2 percent of respondents were from the University of Technology and Applied Sciences (UTAS), Salalah. Table II gives the specific sociodemographic breakdown.

TABLE II SOCIO-DEMOGRAPHIC DETAILS

Demographic Variables	Categories	Frequency	Percentage (%)
Gender	Female	67	50.4%
	Male	66	49.6%
Age Group	Below 15 Years	1	0.8%
	16–17 Years	3	2.3%
	18–20 Years	64	48.1%
	Above 20 Years	65	48.9%
Year of Study	Foundation	28	21.1%
	1st Year (Diploma)	36	27.1%
	2nd Year (Diploma)	37	27.8%
	3rd Year (Advanced Diploma)	13	9.8%
	4th Year (Bachelor)	17	12.8%
	Others	2	1.5%
Major / Area of Study	Arts	22	16.5%
	Engineering	64	48.1%
	Business Studies	47	35.3%
Institution	UTAS – Salalah	124	93.2%
	Others	9	6.8%

3.5. Data Analysis

This study explored the relationships between the constructs and also assessed the model's predictive value using PLS-SEM. This approach was found to be effective for hypothesis testing as well as for advanced non-linear prediction, aligning with the objective of this research in education technology. In the first step, the measurement model was assessed for validity and reliability using PLS-SEM. The structural model was then tested by estimating the path coefficients between the latent constructs. Because of its versatility in handling non-normal data, its ability to handle small to medium sample sizes, and its resilience in developing theories, especially when models incorporate multiple constructs and intricate relationships, PLS-SEM is a good fit for this study (Sarstedt et al., 2017).

IV. MODEL ASSESSMENT IN PLS-SEM

This was done in the analysis of the measurement and the structural models using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 in this research. The evaluation was done in two separate phases. Assessing the outer model in the first stage is done by testing indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. These verifications demonstrated that both the constructs and their indicators were indeed valid and reliable in measuring the theoretical aspects that were formulated in the model (Parasuraman et al., 1988).

In the second stage, the study looked at the inner structural model via analysis of the path coefficients, t-values, and p-values, which were obtained from a bootstrapping procedure that ran 5000 times. The study used this approach, which in turn enabled us to robustly test the put forth relationships. Also, the research looked at the adjusted R^2 values, which was used to determine the model's predictive power. To ensure the robustness and validity of the results the present study also ran collinearity diagnostics (VIF values) which confirmed that multi-collinearity did not play a role in compromise the model estimates (Sarstedt et al., 2019).

4.1 Assessment of the Outer Model

The assessment of the measurement model focused on evaluating internal consistency, reliability, and convergent validity of the constructs (Ab Hamid et al., 2017). The study confirmed internal consistency via Cronbach's Alpha and Composite Reliability (CR). Cronbach's Alpha values ranged between 0.780 and 0.850, and composite reliability values (CR) between 0.872 and 0.909, which are above the 0.70 minimum threshold (Sarstedt et al., 2017). Thus, the study may report that the constructs used in the model are very much internal in terms of their consistency.

Average Variance Extracted (AVE) and indicator loadings. The study reported AVE, which ranged from 0.695 to 0.769 for all, which was above the minimum acceptable value of 0.50, indicating that over half of the variance in the indicators is accounted for by their related constructs (Cheung & Wang, 2017). Also, the individual item loadings were all above 0.822 and in most cases, exceeded 0.85, which in turn confirms the convergent validity of the constructs. As a whole, these results report that the measurement model is very reliable and has high convergent validity, which in turn supports the use of these constructs in our structural model evaluation. The details are presented in Table III.

TABLE III MEASURES OF INTERNAL CONSISTENCY AND CONVERGENT VALIDITY

Construct	Item	Loading	Cronbach's Alpha	rho_A	Composite Reliability (CR)	AVE
Information Quality (IQY)	IQY1	0.855	0.827	0.827	0.897	0.743
	IQY2	0.888				
	IQY3	0.843				
Net Benefits (NBT)	NBT1	0.835	0.780	0.781	0.872	0.695
	NBT2	0.842				
	NBT3	0.824				
Service Quality (SER)	SER1	0.874	0.839	0.839	0.903	0.756
	SER2	0.871				
	SER3	0.863				
System Quality (SQY)	SQY1	0.881	0.850	0.854	0.909	0.769
	SQY2	0.853				
	SQY3	0.896				
Use Benefit (UBT)	UBT1	0.853	0.836	0.850	0.901	0.752
	UBT2	0.853				
	UBT3	0.895				
User Satisfaction (UST)	UST1	0.848	0.805	0.806	0.885	0.720
	UST2	0.875				
	UST3	0.822				

Notes: CR: Composite Reliability, AVE: Average Variance Extracted.

4.2 Evaluation of Discriminant Validity

Discriminant validity is the concern of whether a particular construct is truly identifiable as unique within the model, i.e., in the correlation with other constructs and in the capturing of other phenomena not represented by other variables. In this case, the validity of the discriminant was established with the Fornell-Larcker criterion, a popular PLS-SEM approach to evaluate construct uniqueness (Fornell & Larcker, 1985). The criterion states that for each latent construct, the square root of the Average Variance Extracted should be larger than the greatest correlation it has with any other construct in the model. This ensures that the construct captures more variance with its indicators than with other constructs.

Table IV shows that the square root of the AVE values (which are reported on the diagonal) is greater than the off-diagonal inter-construct correlation values in their respective rows and columns. For example, the square root of the AVE for System Quality (0.877) is greater than its correlation with Information Quality (0.765) and Service Quality (0.731). The study identified a similar trend for all constructs, which in turn confirms that each construct has adequate discriminant validity. Thus, based on the Fornell-Larcker criterion, it is presented that the constructs used in this model are indeed separate and valid for use in the structural model assessment.

TABLE IV DISCRIMINANT VALIDITY – FORNELL–LARCKER CRITERION

Construct	IQY	NBT	SER	SQY	UBT	UST
IQY	**0.862**					
NBT	0.651	**0.834**				
SER	0.726	0.718	**0.870**			
SQY	0.765	0.640	0.731	**0.877**		
UBT	0.599	0.721	0.591	0.551	**0.867**	
UST	0.580	0.814	0.654	0.592	0.689	**0.849**

Note: The boldfaced square root of the AVE of every construct is more than the correlation coefficient in corresponding rows and columns, which justifies the discriminant validity of the scales.

4.3 Evaluating Multicollinearity Using the VIF Measures

In order to evaluate the presence of multicollinearity between indicators, the VIF was calculated for every single item in the measurement model. (Sarstedt et al., 2017) indicate that VIF values smaller than 5.0 can be accepted and would imply that no severe multicollinearity exists. Looking into Table V, it can be observed that the item-level VIF values for each of the units range from 1.577 to 2.305. These are all lower than the critical value. Hence, there is no multicollinearity problem associated with the model underlying the measurement, while the constructs are distinguishably different in their contribution to variance. Therefore, the data affirms that the model estimates are robust and reliable, enabling further structural evaluations without the risk of inflated standard errors induced by multicollinearity.

TABLE V MULTI-COLLINEARITY STATISTICS (VIF VALUES)

Indicator	VIF	Indicator	VIF
IQY1	1.878	UBT1	1.89
IQY2	2.247	UBT2	1.925
IQY3	1.751	UBT3	2.036
NBT1	1.62	UST1	1.827
NBT2	1.643	UST2	1.97
NBT3	1.589	UST3	1.577
SER1	2.042	SQY1	2.051
SER2	2.015	SQY2	1.946
SER3	1.881	SQY3	2.305

4.4 Assessment of the Structural Model (Inner Model)

In order to evaluate the explanatory power of the structural model, key endogenous constructs were analyzed for R-squared (R^2) and adjusted R-squared values. These values measure the accuracy of prediction from the model in comparison to actual results and represent the extent of variance in dependent constructs that is accounted for by independent constructs in the structural path model (Sarstedt et al., 2017). In line with the PLS-SEM procedure, the significance of path coefficients and hypothesis support was checked by bootstrapping with 5,000 resamples. The cross-sections of dependent variables display moderate to substantial predictive power, particularly within social science disciplines where benchmarks for R^2 of 0.25, 0.50, and 0.75 are classified as weak, moderate, and substantial value, respectively (Hair et al., 2017).

According to Table VI, there is a high degree of predictive power because the R2 value for Net Benefits (NBT) is 0.712 and the adjusted R2 value is 0.708. Both User Satisfaction (USt) and Use Benefits (UBT) have R2 values of 0.462 and 0.413, respectively, indicating that the structural model has a moderate predictive relevance for these constructs.

TABLE VI R^2 AND ADJUSTED R^2 VALUES FOR ENDOGENOUS CONSTRUCTS

Construct	R-square	Adjusted R-square
Net Benefits (NBT)	0.712	0.708
Use Benefit (UBT)	0.413	0.400
User Satisfaction (UST)	0.462	0.450

Note: Predictive power of the structural model was interpreted based on adjusted R^2 values.

4. 5 Effect size (f^2) and predictive relevance (Q^2_predict)

To determine the effect of each exogenous variable on the end, which is that of the endogenous variables, we calculated the effect size (f^2). As per Cohen's (1988) report, which in turn reports that effect sizes of 0.02, 0.15, and 0.35 are to be interpreted as small, medium, and large, respectively, the study results. In this study, it is noted that the largest effect size was between User Satisfaction (UST) and Net Benefits (NBT), with a value of 0.666, which is a large effect. Also, it is observed that a moderate effect size of 0.169 for the association between Use Benefit (UBT) and Net Benefits (NBT), while other variables such as Service Quality (SER) and Information Quality (IQY) had small effects on User Satisfaction (UST) at 0.136 and 0.058, which are the values of f^2. There was no significant effect observed from System Quality (SQY) in terms of its role in Use Benefit (UBT), which had an f^2 of 0.006, and also in User Satisfaction (UST) in which it had a very low f^2 of 0.020, which in turn suggests that it does not greatly predict.

The relevance of the model was checked using the Stone-Geisser Q^2_predict criterion (Geisser, 1975; Stone, 1974). As indicated in the self Q^2_predict values obtained from PLS-SEM, all endogenous indicators (NBT, UBT, UST) showed Q^2 values significantly greater than 0, supporting the predictive relevance of the model (Shmueli et al., 2019). For example, the Q^2_predict values for NBT1 (0.318), NBT2 (0.392), and NBT3 (0.365) are exemplary for the Net Benefits construct. Indicators of Use Benefit (UBT1-UBT3) and User Satisfaction (UST1-UST3), as well as other indicators, also showed Q^2_predict values between 0.244 and 0.347, thereby supporting the predictive power of the model. Also, RMSE and MAE values obtained from the PLS-SEM methodology for all indicators were lower than the values yielded from LM, indicating that the PLS-SEM model outperformed the linear regression both in predictive accuracy and model validation.

4.6 Results of Hypothesis Testing and Model Fit

To study the proposed relationships between the variables, a path coefficient analysis was used, which used the bootstrapping method for 5000 resamples in SmartPLS 4. The output presented in Table VII represents the results of the hypothesis testing, which include path coefficients (β), standard error, t-values, and p-values. Of the total hypotheses proposed, some path results were statistically significant. Information Quality (IQY) was found to have a large and positive effect on Use Benefit (UBT) (β =0.309, t = 2.278, p = 0.023), while its effect on User Satisfaction (UST), although present, was not significant (β = 0.135, t =1.032, p = 0.302). Also, we saw that Service Quality (SER) has a large-scale impact on both UBT (β= 0.291, t = 2.145, p = 0.032) and UST (β = 0.428, t = 3.983, p = 0.001). But System Quality (SQY) did not play a large role in either of the two variables looked at (β = 0.102, t = 0.749, p = 0.454) for Use Benefit, and also did not do so for User Satisfaction (β = 0.176, t = 1.585, p = 0.113).

Both Use Benefit (UBT) (β = 0.305, t = 3.518, $p < 0.001$) and User Satisfaction (UST) (β = 0.604, t = 8.676, $p < 0.001$) demonstrated robust and statistically significant positive effects with regard to the outcome variable Net Benefits (NBT). Therefore, according to the significance threshold ($p < 0.05$), five of the eight hypotheses were supported.

TABLE VII RESULTS OF HYPOTHESIS TESTING (BOOTSTRAPPING METHOD, N = 5000)

Hypothesis	Path	β	Std. Dev.	t-value	p-value	Result
H1	IQY → UBT	0.309	0.136	2.278	0.023	Supported
H2	IQY → UST	0.135	0.131	1.032	0.302	Not Supported
H3	SER → UBT	0.291	0.136	2.145	0.032	Supported
H4	SER → UST	0.428	0.107	3.983	0.000	Supported
H5	SQY → UBT	0.102	0.136	0.749	0.454	Not Supported
H6	SQY → UST	0.176	0.111	1.585	0.113	Not Supported
H7	UBT → NBT	0.305	0.087	3.518	0.000	Supported
H8	UST → NBT	0.604	0.070	8.676	0.000	Supported

In Fig. 2 assessing the overall model fit, multiple goodness-of-fit indices were applied. As explained by (Henseler et al., 2016), Standardized Root Mean Square Residual (SRMR) is essential to model fit and is considered acceptable if below 0.08. In this study, SRMR for the saturated model was obtained at 0.063, indicating a good model fit as it is well below the threshold. On the other hand, the SRMR of the estimated model (0.087) was slightly above the optimal cutoff, indicating moderate fit. d_ULS (1.299) and d_G (0.581) alongside Chi-square (424.501) also provided adequate fit, staying within acceptable bounds.

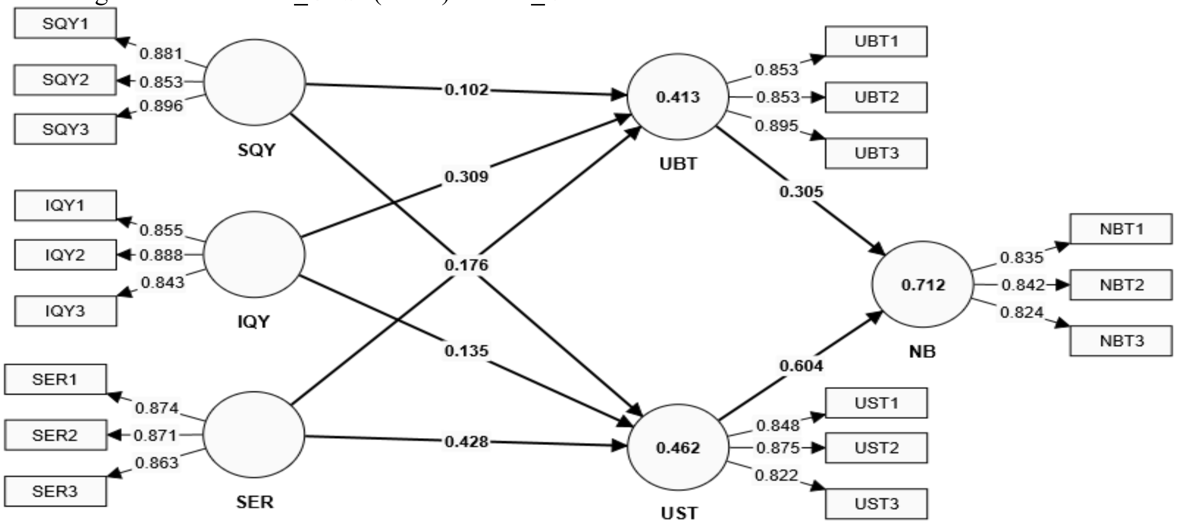

Fig. 2 Structural Model

V. Results and Discussion

5.1 Results

This research aimed at an empirical evaluation of a framework regarding the factors influencing student adoption and satisfaction with AI use in higher education institutions, focusing on UTAS–Salalah in Oman. Based on the DeLone and McLean Information System (IS) Success Model (DeLone & McLean, 2003a) and corresponding with the Stimulus–Organism–Response (S-O-R) theory (Russell & Mehrabian, 1977), at the same time, the model analyzes the impact of system-related stimuli, specifically Information Quality (IQY), System Quality (SQY), and Service Quality (SER), on Use Benefit (UBT), User Satisfaction (UST), and subsequently, Net Benefits (NBT).

Information quality and service quality had significant positive effects on use benefit, according to the structural model tested using PLS-SEM with 5000 bootstrapped samples. This supports the idea that encouraging student interaction with AI tools requires clear content and support accessibility (Sarstedt et al., 2017). Additionally, service quality was found to be a powerful predictor of user satisfaction, indicating that students' favorable opinions are strengthened by timely and informed technical support.

However, in the present study, System Quality was not found to have a statistically significant impact on Use Benefit or User Satisfaction. This suggests that although system reliability and interface ease of use are valuable, these elements by themselves do not improve student outcomes, which instead may require the support of relevant and supportive content, also a result which is in agreement with past research in digital learning settings (Wang et al., 2016). Also, the study found that both Use Benefit and User Satisfaction played a large and positive role in Net Benefits, which in turn supports the idea that the overall user experience has a great impact on academic value, such as better learning results and production (Singh et al., 2022). This also reinforces the success of the IS Model, which emphasizes that user satisfaction and system usage are essential preconditions for system success.

The adjusted R^2 values report that the model does in fact have great explanatory power, it it noticed that Net Benefits (R^2 0.708) has high predictiveness and that although Use Benefit (R^2 0.400) and User Satisfaction (R^2 0.450) do display predictive relevance they do so only at a moderate level (Hair et al., 2017). Also, it is found that the Q^2_predict values, which all came out positive, supported the model's predictive validity and that f^2 effect sizes, which looked at identified User Satisfaction (f^2 0.666), were the most influential variable in Net Benefits (Shmueli et al., 2019). As a whole, content quality and support services play a greater role than does technical performance in the adoption and benefits from AI in education, which in turn gives practical advice to educational technology companies and university administrators trying to improve AI tool performance, user experience, and academic results. This provides actionable insights.

5. 2 Discussion

Using the Stimulus Organism Response (S-O-R) framework, the study examined how technical and service-related stimuli influence student benefit and satisfaction in the adoption of AI tools in higher education (Russell & Mehrabian, 1974). The study examined Stimuli, including System Quality, Information Quality, and Service Quality, which were postulated to influence internal organism evaluations of Use Benefit and User Satisfaction, both of which in turn contribute to the response of Net Benefits. The model present here is a theory that improves the understanding of user technology interaction in digital mediated learning settings.

In terms of benefit results, User Benefit and User Satisfaction emerged as key drivers of Net Benefits demonstrating positive experiences and habitual use contribute to the creation of value. The findings support the IS Success Model put forth by DeLone McLean (2003) which emphasizes that system success is preconditioned by user satisfaction and actual system use. Also, it is the case that User Satisfaction proved to be the best predictor of Net Benefits we see a large effect size (f^2 0.666) which in turn puts forward the idea that the emotional and cognitive user response to AI tools is what in large part determines their success.

The integration of Q^2_predict and other model fit measures further validates the predictive power and the integrity of the model. Regarding SRMR, it was noted that the value registered for the saturated model equals 0.063, which is well below the norm cutoff of 0.08 (Henseler et al., 2015). This gives more confidence around the relationships construct and the model's value measurement in practice. Thus, the study adds to the critique of the S-O-R theory in combination with the IS Success Model concerning investigation of technology adoption in education. It reiterates that user experience governed by quality of support and content is a stronger influencer of success than the system's infrastructure. Therefore, educator and ed-tech developers need to focus on user-driven design, content that aids and robust support that boosts user satisfaction, and building better long-term AI-based learning tools.

5.3. Theoretical Implications.

This research contributes to the existing body of work on educational technology adoption by integrating the DeLone and McLean IS Success Model into the Stimulus Organism Response theory framework. By employing both models, the study represents a comprehensive analysis of how system-based stimuli Information Quality, System Quality, and Service Quality) significantly impact in the organisms' level responses, namely student's Use Benefit and User Satisfaction) which in turn leads to academic success (Net Benefits).

The present study reports on the introduction of the IS Success Model as a shift from previous applications. Until now, the model has been used in business and organizational settings (DeLone McLean, 2003) in contrast, the study applies the same in the higher education field, specifically in the context of AI assisted learning. Further, past research has been mostly on the use of tech in admin or corporate settings (DeLone McLean, 2003), whereas the current study examines the pedagogical issues related to the use of AI tools from a student cantered perspective. Additionally, new insights are presented on how the elements of quality as perceived by students in turn influence their level of engagement and academic results.

Besides that, understanding the model with respect to the S-O-R paradigm enables the study to sustain the environmental stimuli (stimulus) technology quality factors as environment stimuli. This triggers internal evaluations (organism) like satisfaction and habitual usage that results to behavioral outcomes (response)—perceived educational benefits. This deepens the S-O-R theory's applicability in understanding digital learning and further highlights the rich possibilities of psychological frameworks for studying technology influenced academic behavior. Moreover, the case study students from a public university in Oman represent a regionally significant but underutilized perspective in the literature on information systems and education technology from the Global South. These findings indicate that emerging market cultures, technologies, and institutions can autonomously shape and modulate the processes of technology acceptance, which requires greater scrutiny of cross-cultural applications of these theories. This contribution could be strengthened in future studies by investigating other constructs like self-efficacy, trust, or technostress, as well as by looking at longitudinal effects to record consistent usage patterns over time.

5.4 Managerial Implications

The results of the research provide key management lessons for Higher Education Institutions (HEIs) as they seek to improve the use and outcomes of AI tools in academic settings.

As HEIs all over the world and in particular in emerging markets like Oman, this study proposed a framework to bridge the gap between the implementation of technological infrastructure and the achievement of quality educational outcomes. Also of primary importance is that HEIs focus on Information Quality and Service Quality which in turn will greatly improve student interaction with AI tools. This implies the output generated by AI has to be relevant, accurate and appropriate to the academic setting. Additionally, technical and instructional support staff must be readily available, responsive and well trained. Without parallel investment in student centered support systems which pay attention to the whole student experience, it is not possible to see large scale educational value from AI.

Further, it was found out that System Quality doesn't in large scale translate to greater student use or satisfaction. It is not suffiecient to simply implement AI infrastructure, HEIs must ensure the inclusion of inuitive features, multi-language support, and seamless integration of new platforms with existing learning management systems to achieve meaningful use. From a strategic stand point it is suggested that admin should be in to foster a culture of digital fluency among faculty and students. Workshops, orientation programs and integration of AI tools should be implemented to demystify these technologies and build student confidence in their use. This in turn may play a significant role in increasing Use Benefit and User Satisfaction both of which contribute to the net benefits such as better academic performance, better use of resources, and enhanced personalized learning.

Moreover, universities and colleges (HEIs) need to create responses and assists channels which allow students to receive help as issues arise since, in this case, Service Quality has the highest impact on User Satisfaction in this research. Clearly, digital assist technologies and help among students need to be more humane and engaging in order to foster and enable users to maintain use over time. Lastly, conclusions from this study motivate HEIs to rethink their digital frameworks and artificial intelligence (AI) technologies with calibrated lenses, focusing not on the blindfolded advancements in technology, but on students' experience and perception. It is crucial that these decision makers set up systems to gather data on students' experiences with AI technology continuously, and analyze whether the value from the technology being used is worth the cost. All things considered, AI in education needs to be viewed as a service as well as a technical advancement. Higher education institutions that prioritize high-quality content, user-friendly systems, and robust support networks will be in the best position to accomplish significant digital transformation and improve student achievement.

VI. CONCLUSION

This study examined the factors determine AI tool adoption and their impact on student outcomes in higher education in the case of UTAS Salalah. The research grounded in DeLone and McLean IS Success Model viewed through the Stimulus Organism Response framework. The findings indicate that Information Quality, Service Quality to a lesser extent, system quality significantly shape student use behaviour and user satisfaction which in turn drive the main benefits of AI tools adoption. Among the key results, Information Quality and Service Quality came out as the best predictors of Use Benefit and User Satisfaction which in turn stresses the role of relevant content, accuracy and responsive support in getting engagement. Additionally, System Quality was found to play limited role suggesting technical function alone is not enough for wide scale adoption without also having pedagogical and support elements.

The study also reported that User Satisfaction and Use Benefit are key factors influencing perceived Net Benefits supporting idea that student interaction and positive emotional response to AI tools ultimately produce academic including improved learning efficiency, better comprehension, and improved performance. These results have large scale implications for higher education institutions (HEIs) which are to implement or scale AI tools for academic support. Institutions must not only put in the technology but also create a support which is rich in resources and content which is student and user centered.

The model's performance is demonstrated by high R^2 values and supported by Q^2_predict and low SRMR indicating its robustness in terms of its ability to capture complex relationships between system elements, user experience and outcome perceptions. Though this study does add to theory and practice in meaningful ways it is important to note its limitations. The present study explored a substantial sample of respondents (n 133) from one of the branches of UTAS, a leading and largest higher education institution in Oman, although the foucs on a single academic setting may limit the broader generalizability of the findings. For future research, it is proposed to use larger and more varied samples which span multiple regions or institutions and also suggest the inclusion of additional variables such as trust, digital fatigue, self-efficacy, or cultural elements which in turn will better enrich the model.

Finally, implementing AI tools in education is a student-centered change rather than just a technical one. HEIs must rethink their AI integration strategies from the perspectives of emotional resonance and quality experience in order to guarantee a significant, long-lasting influence on the learning process.

VII. LIMITATIONS AND FUTURE RESEARCH

This study reports on what we found in terms of student adoption and satisfaction of AI tools in higher education which is to be taken as a report of our results which also has its limitations. First, the data for this study was collected from students at the University of Technology and Applied Sciences (UTAS) in Salalah, Oman. As institutional, cultural and technical settings may differ greatly between regions and universities the results may not be applied beyond this setting. What we suggest for future research is to repeat this study in other institutions and across countries which also include diverse geographic areas. Thus, via this we may obtain a more in-depth picture of AI use in higher education.

Second, the study used a non-probability purposive sampling which went after students that had past experience with AI in academic settings. While that method worked for us in terms of identifying appropriate subjects it also introduced bias which in turn limited the generalization of our results. In the future we suggest you use random or stratified sampling which crosses departments and academic levels to improve the representativity of the sample.

Third, the current model was cross sectional in design which we filled via self-report in an online questionnaire. While the digital survey method made for easy distribution it did not may fully report the in-depth student experiences or issues in real time in the learning environments. In the forthcoming studies researcher can look at mixed methods which include interviews or class room-based observations to add to the picture and also to see in what ways our quantitative results play out. In total while we put forth a base model which looks at AI use in higher education this study also puts out a call for research that looks at wider and more diverse groups, uses multiple methods of data collection, and looks at a greater range of theories to in turn get deeper insight and to see how the results play out in a greater array of educational settings.

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