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Automated Academic Advisory System Based on Students' Emotional Intelligence: A Study of University of Nizwa, Sultanate of Oman

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Abstract: The COVID-19 pandemic has brought outward unparalleled difficulties in the field of education, emphasizing the need for unique solutions. This study aimed to evaluate the determinants that affect the effective implementation of the automated student academic advisory system at the University of Nizwa of the Sultanate of Oman, with a particular emphasis on its influence on students' emotional intelligence during the pandemic The research utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) model to investigate how factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions influence students' behavioral intentions. In addition, the study examined the behavioral intention effects on the use of the automated system, emotional intelligence effects and the experience of COVID-19 specifically influences the actual use of the system. The study employed a case study methodology in combination with a quantitative survey method to gather data from 272 students and advisors at the University of Nizwa. The collected data was analyzed using SmartPLS, a technique known as structural equation modeling. The research provides useful information on the adoption of technology in an educational environment and its impact on student well-being and emotional intelligence. The study found that only performance expectancy and facilitating condition factors had a substantial impact on behavioral intention, whereas effort expectancy and social influence did not. Behavioral intention showed a positive correlation with actual usage, but performance expectancy, effort expectancy, and social influence did not directly influence the actual utilization. Moreover, behavioral intention served as a mediator for the indirect impact of performance expectancy and facilitating conditions on actual usage. However, it did not mediate the indirect impact of social influence and effort expectancy on actual utilization. Furthermore, the impact of COVID-19 and emotional intelligence did not influence the relationship between facilitating conditions and actual use. These findings offer valuable information into understanding educational technology, particularly in situations of global crises, and offer practical recommendations for educators, legislators, and academic institutions seeking to enhance student participation, support, and general well-being.

Keywords: Automated Student Academic Advisory System, COVID-19 Pandemic, Emotional Intelligence, UTAUT Model, University of Nizwa

1. INTRODUCTION

Technology is employed in the provision of academic advice. Academic advising services in higher education are being streamlined and improved using web-based solutions. This adoption streamlined course selection and enhanced counselors' ability to track students' academic achievement [1]. COVID-19 has improved online student services. Universities needed to improve academic advising through technology. The expansion of learning made it more adaptable, and accessible and improved the advisor-student relationship [2]. In Oman, education is valued at the national, local, and individual levels. Many governments fund education in part because it benefits society and individuals. Due to competing public fund needs, education must be delivered efficiently, particularly during the global financial crisis [3]. When outcomes are maximized while using fewer resources, education is efficient. University students frequently struggle to select courses that align with their career and educational objectives. They are unable to assess how their course selections would affect their accomplishment and CGPA, suggesting a mismatch between Oman's Ministry of Education's aspirations and educational outcomes [4].

COVID-19 (June 2020) advanced online academic classes and student services. During this unique age, technology became more crucial for academic therapists, but certain institutions with limited resources had difficulty transitioning to online services [5]. Universities in the Middle East, particularly in Oman, strive to achieve international standards. In advising systems, students and advisers must carefully plan for academic success. Many universities around the world use computerized academic advice [6]. Online student advising effective forms are understudied. Academic advice, which is critical to student success, has been overlooked [7].

This study examines how an automated student academic advisory system at the University of Nizwa, Oman, affects students' emotional intelligence during the COVID-19 epidemic. Using the Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm in many contexts, including educational institutions, the study demonstrates its flexibility and depth. [7].

2. LITERATURE REVIEW

This study investigates why higher education institutions embrace automated technologies for student advisory services. The purpose of this study is to investigate the effects of variables based on UTAUT. These include performance expectancy, effort expectancy, social influence, facilitating factors, and automated system usage intention. This study's use of emotional intelligence and the COVID-19 instrument to assess real-world technology use is intriguing.

COVID-19 has had a major impact on students' mental and emotional wellness. Multiple studies have found increased melancholy, anxiety, and stress among university students at this difficult time. Hassan [9] found that 33% of Saudi students felt negatively affected by the epidemic, with female and average academic performers more affected. Another study, by Iqbal [10] found that students' emotional intelligence, particularly self-regulation and self-awareness, improved their academic performance during the pandemic, both directly and indirectly through academic social networking sites. Another study by Puraivan [11] developed an emotion-based decision-support tool to help virtual learners manage their emotions and recognize their feelings. Capone [12] created an adaptive e-learning system to help students throughout the crisis, increasing situational awareness and reducing frustration.

The pandemic, on the other hand, has impacted student learning. Ghazawy [13] discovered that 70.5% of Egyptian students were depressed, 53.6% were anxious, and 47.8% were stressed. Female students, those who knew someone who was infected, those who had chronic illnesses, and those who did not have family or university support were more likely to have psychological problems. Sánchez-Cabrero [14] found no link between social isolation and children's emotional intelligence, test anxiety, or academic achievement after the epidemic. Baloran [15] discovered that students were unsatisfied with online learning and adopted a variety of coping techniques. During pandemics, Kaplan-Rakowski [16] proposed prioritizing students' emotional needs over efficiency and offering video feedback in addition to textual information, which can signify social presence and support. These studies show that the pandemic has had a significant impact on the well-being and learning experiences of university students, emphasizing the necessity for specific treatments and adaptations.

2.1. Theoretical Review

In this study, the Unified Theory of Acceptance and Use of Technology (UTAUT) is used and applied because it can assess user behavior across computer technologies and populations. Its simplicity and strong theoretical foundation make it ideal for this research [8]. The model has four main components Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions. PE examines the user's perception of a technology's benefits to determine its usefulness. EE investigates the technology's perceived simplicity. SI emphasizes social norms and peer influence by indicating how family, friends, and coworkers influence a user's technology choice. The last construct, FC, shows an individual's sense of technical and organizational support, revealing ambient and situational aspects that can help or hinder technology adoption.

2.1.1. Actual Use of the Automated Student Academic Advisory System

The automated student academic guidance system's practical use is the ultimate goal for all users. Robey [19] examined 66 salespeople's usage of a computerized record-keeping system using Schultz and Slevin's [20] attitude instrument. Actual use indicators were compiled using data provided by the company and then connected. Two of the seven Likert segments were taken out of consideration because of their low levels of internal dependability. There was a correlation between both utilization measures and the remaining five subscales (link 6), with the 'performance' subscale having the strongest connection (Spearman correlations =.79 and.76). even though performance and perceived usefulness were quite comparable to one another, performance was employed as an attitude variable even though attitudes were not measured separately.

2.1.2. Performance Expectancy (PE)

As per Venkatesh [8], it is believed that a system or technology will improve job performance. In the TAM, perceived usefulness (PU) is the likely user's observation that applying a particular application system will improve their organizational work performance [18]. It is hypothesized to positively influence the behavioral intention (BI) of both students and student advisers in adopting an automated student academic advisory system at the University of Nizwa in the Sultanate of Oman, considering its effect on students' emotional intelligence during the global epidemic caused by COVID-19. It hypothesizes as follows:

H1: Performance expectancy will positively impact the behavioural intention to use the automated student academic advisory system in the UN, looking at its impact on the student's emotional intelligence during the COVID-19 pandemic.

2.1.3. Effort Expectancy (EE)

Effort expectancy (EE) is the ease of using a system [8], equivalent to PEU in TAM. PEU evaluates how much the prospective user has an expectancy that the system will be simple to use [18]. This depends on the technology and its design, but it can also depend on personal aspects like a willingness to learn and adapt [21]. Numerous ICT use studies show a strong association between effort expectancy and technology adoption. Soong [22] found that effort expectancy positively affects SMEs' private sector electronic government procurement uptake. Similarly, Lutfi [23] found that effort expectancy positively affected SMEs' accountants' intention to use the new accounting information system. This leads to this research's hypothesis:

H2: Effort expectancy will positively affect the behavioural intention to use the automated student academic advisory system in the UN, looking at its impact on the student's emotional intelligence during the COVID-19 pandemic.

2.1.4. Social Influence (SI)

According to Venkatesh [8], The term "social influence," abbreviated as "SI," refers to the degree by which a person's believes others consider a new system essential. Users' perceptions of family and friends adopting technology are important [24]. Social influence includes how others shape an individual's feelings, views, and behaviors. This study includes Social Influence (SI) as an independent variable, as in many studies on technology adoption and it is hypothesized as

H3: Social influence positively impacts the behavioural intention to use the automated student academic advisory system in the UN, looking at its impact on the student's emotional intelligence during the COVID-19 pandemic.

2.1.5. Facilitating Condition (FC)

The term "Facilitating Conditions" (FCs) refers to the degree to which a person thinks that the institutional and technological basis of a system facilitates the utilization of that system [8]. Facilitating conditions are the extent to which an organization offers the technical infrastructure needed for e-business. Facilitating conditions significantly impact a business institution's financial information system adoption, according to [25]. The following hypotheses follow:

H4: Facilitating conditions will positively affect the behavioural intention to use the automated student academic advisory system in the UN, looking at its impact on the student's emotional intelligence during the COVID-19 pandemic.

2.1.6 Behavioural Intention (BI)

Behavioural Intention (BI) is a person's preparedness to act [8]. The amount to which a person thinks they will do something. Within the scope of this study, researchers investigate the factors that determine the University of Nizwa's automated student academic advice system's use and its impact on students' emotional intelligence during the COVID-19 epidemic, it is hypothesized as:

H5: Behavioural intention directly positively affects the actual use of the automated student academic advisory system at the UN in the Sultanate of Oman, looking at its impact on the student's emotional intelligence during the COVID-19 pandemic.

H6: Behavioural intention mediates the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions of the actual use of the automated student academic advisory system at the UN, looking at its impact on the student's emotional intelligence during the COVID-19 pandemic.

2.1.7 Emotional Intelligence (EI)

Emotional intelligence (EI) is the capacity to identify, comprehend, manage, and make effective use of one's own and other people's feelings and behaviors in a variety of everyday settings is known as emotional intelligence (EI). Self-awareness, Self-control, empathy, and the ability to interact with others are all important to interpersonal connections, decision-making, and personal well-being [26]. This study examines whether the automated student academic advise system at the University of Nizwa, Oman, moderates the relationship between conducive conditions and system usage. So Emotional Intelligence (EI) is a hypothesis.

H7: Emotional intelligence moderates the effect of facilitating conditions on the actual use of the automated student academic advisory system at the UN, looking at its impact on the student's emotional intelligence during the COVID-19 pandemic.

2.1.8 COVID-19 Experience (C-19E)

The COVID-19 epidemic disrupted worldwide supply networks and the aviation industry, making it difficult to estimate its economic impact, according to [27]. The COVID-19 pandemic has caused medical care shortages, budgetary difficulties, and major setbacks in vulnerable areas like tourism, logistics, and civil aviation, making it difficult to quantify its economic impact. Technology adoption researchers have not examined COVID-19 as a moderating variable, like emotional intelligence so this study examines the COVID-19 moderating impact on facilitating condonation and it is hypothesis as:

H8: The experience of COVID-19 moderates the effect of facilitating conditions for the actual use of the automated student academic advisory system at the UN, looking at its impact on the student's emotional intelligence during the COVID-19 pandemic.

2.2. Proposed Model

The following research model was proposed by this study based on the literature evaluation that was presented earlier in the sentence (see Figure 1) focused on assessing the factors that influence the practical implementation of the automated student academic advisory system at the University of Nizwa in the Sultanate of Oman, specifically emphasizing its impact on students' emotional intelligence during the pandemic.

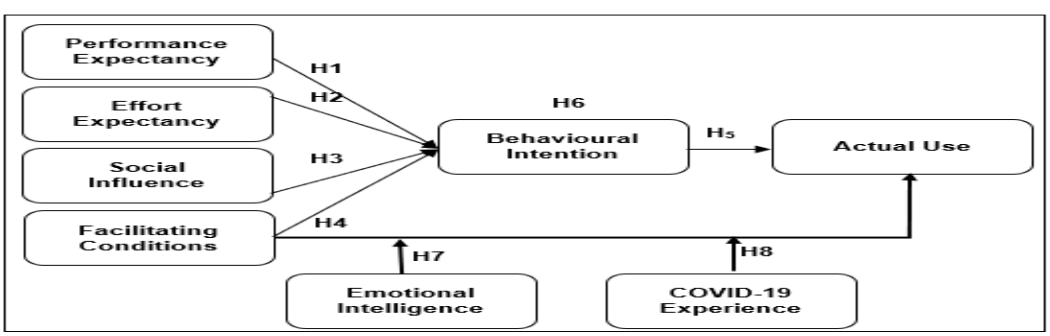

Figure-1. Proposed Model

3. RESEARCH METHODOLOGY

Using a quantitative methodology, the study examined how the University of Nizwa in Oman uses its automated student academic advisory system. The UTAUT model guided the study. Surveys were used to obtain data. UTAUT, its extensions, and academic advising and emotional intelligence literature informed the questionnaire's creation. Study participants included University of Nizwa students and academic advisers selected using purposive sampling [28]. According to Slovin's calculation, 272 valid replies were obtained from 300 questionnaires. The study instrument was pilot-tested to improve reliability and validity. Research methodologies and tools were modified based on test findings [29]. The research used SmartPLS software for partial least squares structural equation modeling (PLS-SEM) data processing. The analysis involved evaluating measurement and structural models and testing hypotheses and research questions [30].

4. RESULTS AND DISCUSSION

4.1 Demographic Profiles of the Respondents

In the current study, the demographic profiles of the respondents were analyzed and characterized based on eight different categories. The breakdown of demographic profiles of the respondents includes gender, age group, student status, academic level, Family's annual revenue, academic year, Colleges and Institutes, and types of automated devices used from your home during the COVID-19 pandemic for academic purposes. Table 1 below presents more of the statistical details.

Table-1. Demographic profiles of respondents

Categories	Frequency	Percentage (%)
What is your gender?		
Male	136	50.0
Female	136	50.0
What is your age group?		
Below 20 years	154	56.6
21-34 years	25	9.2
35-44 years	93	34.2
Which type of student are you?		
Local from Oman	252	92.6
International from Abroad	20	7.4
What is your academic level?		
Diploma or other related certification	82	30.1
Undergraduate degree	190	69.9
What is the range of your family's annual revenue?		
Bellow 40,000 OMR	232	85.3
40,000 to 50,000 OMR	19	7.0
51,000 to 60,000 OMR	8	2.9
61,000 to 70,000 OMR	4	1.5
71,000 to 80,000 OMR	3	1.1
Above 81,000 OMR	6	2.2
Which academic year are you in now?		
Year 1	27	9.9
Year 2	46	16.9
Year 3	66	24.3
Year 4	51	18.8
Year 5	38	14.0
Final year	44	16.2
What Colleges and Institutes are you studying at?		
College of Arts and Sciences	29	10.7
College of Economics, Management & Information System	70	25.7
College of Engineering & Architecture	47	17.3
College of Pharmacy & Nursing	21	7.7
Foundation Institute	10	3.7
DHAD Institute for TASOL	5	1.8
Lifelong Learning Institute	5	1.8
Others	85	31.3
Automated devices used from your home during the COVID-19 pandemic for academic purposes?		
Desktop Computer	8	2.9

Categories	Frequency	Percentage (%)
Laptop Computer	143	52.6
Tablets Devices	33	12.1
Smart Phone	61	22.4
Others	27	9.9

A complete demographic breakdown of responders is in Table 1. Half of the responders are male, and half are female. The majority (56.6%) of respondents are under 20, and the majority (92.6%) are Oman-based students. Most responders (69.9%) are undergraduates and hail from families earning less than 40,000 OMR (85.3%). The largest number (24.3%) is in year 3, however, respondents are evenly distributed. The bulk of colleges and institutes are 'Others' (31.3%), followed by the College of Economics, Management, and Information System (25.7%) and the College of Engineering & Architecture (17.3%). The DHAD Institute for TASOL and Lifelong Learning Institute had 1.8% each, the lowest. The most common automated device for academic purposes during the COVID-19 pandemic was a laptop (52.6%), followed by smartphones (22.4%) and tablets (12.1%). Desktop computers were used by 2.9% of respondents. Demographic data is essential for contextualizing respondents' responses and assessing study results.

4.2. Measurement Model Assessment

Measurement models establish observed-latent variable relationships, making them crucial. Assessing the measurement model before the structural model ensures construct validity and reliability [30].

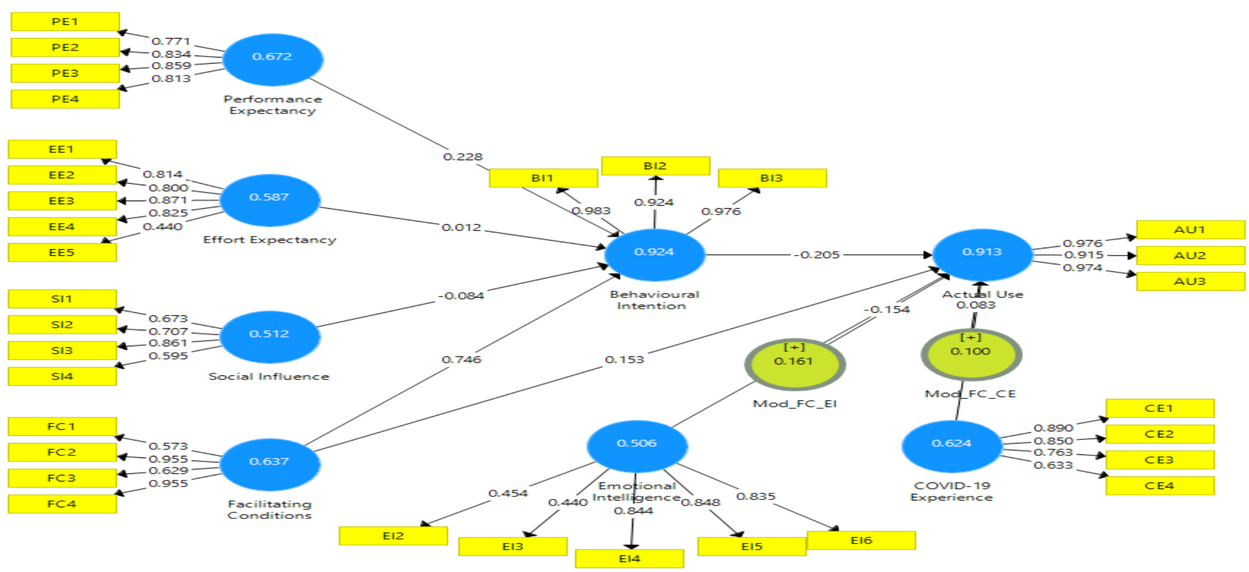

Figure 2. Measurement model

Table 2. Reliability and Validity

Construct	Items	Outer Loading	Cronbach's alpha	Composite reliability	AVE
Actual Use	AU1	0.976	0.952	0.969	0.913
	AU2	0.915			
	AU3	0.974			
Behavioural Intention	BI1	0.983	0.958	0.973	0.924
	BI2	0.924			
	BI3	0.976			
COVID-19 Experience	CE1	0.890	0.806	0.868	0.624
	CE2	0.850			
	CE3	0.763			

Construct	Items	Outer Loading	Cronbach's alpha	Composite reliability	AVE
	CE4	0.633			
Effort Expectancy	EE1	0.814	0.809	0.872	0.587
	EE2	0.800			
	EE3	0.871			
	EE4	0.825			
	EE5	0.440			
Emotional Intelligence	EI1	Removed	0.752	0.826	0.506
	EI2	0.454			
	EI3	0.440			
	EI4	0.844			
	EI5	0.848			
	EI6	0.835			
Facilitating Conditions	FC1	0.573	0.804	0.870	0.637
	FC2	0.955			
	FC3	0.629			
	FC4	0.955			
Performance Expectancy	PE1	0.771	0.837	0.891	0.672
	PE2	0.834			
	PE3	0.859			
	PE4	0.813			
Social Influence	SI1	0.673	0.693	0.805	0.512
	SI2	0.707			
	SI3	0.861			
	SI4	0.595			

The study's construct reliability and validity are assessed in Table 2. Notably, "Actual Use" and "Behavioural Intention" are highly reliable and valid. Strong links between observable variables and latent constructs are shown by outer loadings above 0.9 for these constructs. They also have strong internal consistency with Cronbach's alpha values of 0.952 and 0.958. Their composite dependability scores include 0.969 for "Actual Use" and 0.973 for "Behavioural Intention." In comparison, the "COVID-19 Experience" construct has acceptable reliability with outside loadings of 0.633 to 0.890. "Effort Expectancy," "Facilitating Conditions," and "Performance Expectancy" are reliable and valid. These constructs have outer loadings above 0.8, Cronbach's alpha values from 0.806 to 0.952, and composite reliability scores from 0.870 to 0. 891. Significantly, the "Emotional Intelligence" construct had measurement issues, resulting in one component being removed. Additionally, "Social Influence" has moderate outside loadings, indicating item variability. Optimizing these constructions may improve measurement accuracy. Due to strong outer loadings, high Cronbach's alpha values, and high composite reliability scores, most study constructs are reliable and valid. To improve measurement accuracy, "Emotional Intelligence" and "Social Influence" may need improvement.

Table 3. Discriminant validity using Fornell and Lacker Criterion

	AU	BI	CE	EE	EI	FC	PE	SI
AU	**0.955**							
BI	-0.177	**0.961**						
CE	-0.209	0.558	**0.790**					
EE	-0.152	0.531	0.793	**0.766**				
EI	0.260	0.146	0.120	0.094	**0.711**			
FC	-0.096	0.806	0.563	0.584	0.148	**0.798**		
PE	-0.201	0.594	0.894	0.639	0.098	0.566	**0.820**	

SI	-0.165	0.768	0.811	0.737	0.173	0.898	0.762	0.716

4.3. Structural Model (Hypotheses Results)

To determine the significance level of the path coefficients in the structural model with PLS, the bootstrapping technique was applied. The results of the eight hypotheses tested in the present study are summarized in Table 4. The results showed that Performance Expectancy and Facilitating Conditions significantly positively impact Behavioural Intention. Additionally, Behavioural Intention significantly negatively impacts Actual Use, contrary to what was initially hypothesized. Moreover, Facilitating Conditions indirectly influence Actual Use through their impact on Behavioural Intention, whereas Performance Expectancy, Social Influence, and Effort Expectancy do not. Lastly, neither COVID-19 experience nor emotional intelligence was found to moderate the effect of Facilitating Conditions on Actual Use of the automated student academic advisory system at the University of Nizwa in the Sultanate of Oman, looking at its impact on the student's emotional intelligence during the COVID 19 pandemic. Lastly, the findings suggest that while Performance Expectancy and Facilitating Conditions are vital factors influencing Behavioural Intention to use the automated student academic advisory system, Effort Expectancy, and Social Influence do not play a significant role. Additionally, although Facilitating Conditions indirectly influence Actual Use through their impact on Behavioural Intention, Performance Expectancy, Social Influence, and Effort Expectancy do not. Lastly, the data did not support the hypothesized moderating effects of COVID-19 experience and emotional intelligence on the relationship between Facilitating Conditions and Actual Use.

Table 4. Hypotheses Testing Results

	Path	Beta	Standard deviation	T statistics	P values	Result
H1	Performance Expectancy -> Behavioural Intention	0.228	0.081	2.811	0.005	Supported
H2	Effort Expectancy -> Behavioural Intention	0.012	0.063	0.182	0.856	Not Supported
H3	Social Influence -> Behavioural Intention	-0.084	0.136	0.616	0.538	Not Supported
H4	Facilitating Conditions -> Behavioural Intention	0.746	0.095	7.809	0	Supported
H5	Behavioural Intention -> Actual Use	-0.205	0.093	2.204	0.028	Supported
H6a	Performance Expectancy -> Behavioural Intention -> Actual Use	-0.047	0.026	1.786	0.074	Not Supported
H6b	Social Influence -> Behavioural Intention -> Actual Use	0.017	0.031	0.546	0.585	Not Supported
H6c	Effort Expectancy -> Behavioural Intention -> Actual Use	-0.002	0.014	0.163	0.871	Not Supported
H6d	Facilitating Conditions -> Behavioural Intention -> Actual Use	-0.153	0.073	2.085	0.037	Supported
H7	COVID-19 Experience x Facilitating Conditions -> Actual Use	0.083	0.092	0.902	0.367	Not Supported
H8	Emotional Intelligence x Facilitating Conditions -> Actual Use	-0.154	0.137	1.13	0.258	Not Supported

4.4. Assessment of Coefficient of Determination (R2 Value)

The R^2 coefficient assesses the precision of a statistical model in forecasting results. The dependent variable of the model is the outcome. The value of R^2 can go as low as zero and as high as one at most. The fraction of the variance in one variable that can be accounted for by another variable is represented by the coefficient of determination, which is abbreviated as R^2. The proportion of the total variation in the dependent variable that can be accounted for by the predicted variable is the amount that is determined by the coefficient of determination, also known as R^2. It is computed by taking the square of the correlation that exists between the anticipated construct and the dependent construct. [30]. The coefficient of determination, R^2, calculates the extent to which the independent variable influences the dependent variable [31].

Table 5. R^2 Value

Endogenous construct	R^2	Relationship
Behavioural Intention	0.678	Large effects
Actual Use	0.187	Medium

Table 5 presents the R^2 values for the endogenous constructs of 'Behavioural Intention' and 'Actual Use'. The model's R^2 value of 0.678 indicates that it accounts for 67.8% of the variability in 'Behavioural Intention'. Cohen [32] states that R^2 values of 0.02, 0.13, and 0.26 represent significant explanatory power, with minor, medium, and large effects, respectively. Nevertheless, the R^2 score for 'Actual Use' is 0.187, signifying that the model merely accounts for 18.7% of the variability in this variable. This has limited explanatory efficacy. Although the idea elucidates 'Behavioural Intention,' it does not elucidate 'Actual Use.' This implies that the model may not account for external factors that have a substantial impact on 'Actual Use'. Researchers and practitioners should be aware that the model may not comprehensively encompass all the factors that influence 'Actual Use' and may require further investigation to identify and incorporate them.

4.5. Effect Size (f^2 Value)

Evaluating the effect size (f^2) is essential for assessing the practical influence of independent constructs on the dependent construct. It computes the additional influence of an independent variable on the dependent variable, accounting for the explanatory power of other independent variables in the model. The independent construct computes the magnitude of the f2 effect size. The effect sizes are categorized as small (0.02), moderate (0.15), and big (0.35) according to the studies conducted by Hair [30] and Ramayah [33]. Table 6 displays the relationships between independent and dependent constructs, as well as the magnitude of their impact.

Table 6. f^2 values

Dependent construct	Independent construct	f^2	Effect
Actual Use	Effort Expectancy	0.000	No Effect
	Facilitating Conditions	0.265	Medium
	Performance Expectancy	0.056	Small
	Social Influence	0.002	No Effect

Table 6 displays the f^2 values about the correlation between independent constructs (Effort Expectancy, Facilitating Conditions, Performance Expectancy, and Social Influence) and Actual Use. According to Cohen [32], f^2 values of 0.02, 0.15, and 0.35 represent mild, medium, and substantial effects, respectively. The Effort Expectancy has a negligible f^2 value of 0.000, suggesting that it has no significant impact on Actual Use. The variable of Facilitating Conditions has a moderate impact on Actual Use, as indicated by a f^2 value of 0.265. The impact of Performance Expectancy on Actual Use is minimal ($f^2 = 0.056$), whereas Social Influence has a negligible effect ($f^2 = 0.002$). Facilitating Conditions and Performance Expectancy have a greater impact on the utilization of the automated student academic advising system at the University of Nizwa in Oman compared to Effort Expectancy and Social Influence. The enhancements to the current utilization should mostly concentrate on optimizing the facilitating conditions and performance expectancy.

4.6. Predictive Relevance of the Model (Q2 Value)

Blindfolding permits Stone-Geisser's Q2 value to estimate model predictive relevance [30]. This indicator-based systematic resampling method identifies and removes data values. This method predicts the importance of a dependent construct-based measurement model [30]. With blindfolding, the omission distance (D) guides removed data. Q2 greater than 0 indicates model predictive significance. The blindfolding technique employed D = 7 omission distance in this study. The blindfolding assessment showed that the model has predictive validity because the Q2 values for Actual Use (0.148) and Behavioral Intention (0.615) were significantly above zero.

5. RECOMMENDATIONS

This study yields some recommendations that can enhance the advancement and refinement of the automated student academic advisory system:

1. **Exploration of Additional Factors:** Future research endeavors could investigate deeper into understanding the acceptance and use of the automated system by investigating other influential factors. Factors like trust, perceived risk, and user satisfaction warrant comprehensive exploration to provide a more comprehensive picture of the system's adoption.
2. **Expansion of the Study Scope:** Expanding the research beyond the University of Nizwa to include a broader range of higher education institutions in Oman and other countries would enable comparative analysis. This approach would facilitate the identification of cross-cultural variations and enhance the generalizability of the study's findings.
3. **Mixed-Methods Approach:** Employing a mixed-methods research design would enrich the study by combining quantitative data, as used in this research, with qualitative data. Qualitative insights can offer a deeper understanding of users' perceptions, experiences, and challenges with the automated system, providing a more holistic view.
4. **Long-term Impact Assessment:** To assess the holistic impact of the automated system, future studies could focus on its long-term effects. This might involve an examination of students' academic performance, retention rates, and graduation rates, as well as their emotional intelligence and overall well-being over an extended period.
5. **Stakeholder Feedback:** Besides student feedback, involving academic advisors and other key stakeholders such as faculty members, administrators, and parents in the evaluation process would provide a more comprehensive perspective. This collaborative approach can help assess the system's effectiveness and efficiency from multiple viewpoints, potentially leading to refinements that benefit all parties involved.

6. LIMITATIONS

This study is not without its limitations. Firstly, the research was conducted within the boundaries of the University of Nizwa in the Sultanate of Oman, which possesses unique cultural and educational characteristics. Consequently, the extent to which these findings can be generalized beyond this cultural and institutional context may be limited. Secondly, the methodology employed in this research involved utilizing a survey questionnaire distributed among students and academic advisors at the University of Nizwa. While this approach offers valuable insights, it is not immune to potential sources of bias, sampling errors, and complexities in result interpretation, which may influence the conclusions' robustness. Thirdly, this study predominantly focuses on the technological aspects of academic advising, specifically the Automated Advisor system. While shedding light on the potential benefits of such technology, it may inadvertently downplay or overlook the broader human and sociocultural dimensions that influence the advisor-student relationship. Lastly, this research focuses exclusively on higher education institutions, particularly the University of Nizwa. Consequently, the applicability and transferability of the findings to other educational levels or diverse organizational contexts may be limited. These limitations underscore the need for caution when extrapolating these findings to different settings or educational tiers.

CONCLUSION

This research investigated the factors influencing the use of the Automatic Student Academic Advisory System at the University of Nizwa in the Sultanate of Oman and its impact on students' emotional intelligence during the COVID-19 pandemic. The main objective of this study was to reveal the relationship between behavioural intention and actual use based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and to verify the mediating effect of behavioural intention, the moderating effect of emotional intelligence, and the moderating effect of COVID-19 experience. A questionnaire survey was conducted among students and their academic advisors at the University of Nizwa, and the data were analyzed using Structural Equation Modelling (SEM). The findings from the research deepen theoretical insights into the acceptance and use of Automatic Student Academic Advisory Systems and provide practical implications for educational institutions and policymakers to enhance student engagement, support, and overall well-being. This study also considered the potential and limitations of technology-driven educational tools during the pandemic.

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