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A Hybrid SEM-ANN Model for Post-Pandemic Adoption of Online Platform Using Information and Technology Acceptance Constructs

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***Abstract* - Using the TAM and the information attributes of Information Richness and Information Quality, we study Gulf region universities that make use of online resources during the pandemic. We then employ a dual-stage analytical design to determine their future behavioral intentions. Core behavioral aspects were systemically tapped by use of a cross-sectional survey instrument design. Out of the 638 students surveyed, PU, PEOU, IR, IQ, and BI were sampled (data collected October 25 25- December 25, 2021). Following the basic IR→BI and IQ→BI, the structural model for PLS-SEM (SmartPLS) was adjusted and possesses marked later validation and nonlinear profound artificial neural network rank effects (2 hidden layers, 10-fold cross-validation). The PLS-SEM Model Explained 63.2 on the variance of BI and all the paths IR→BI PU→BI PEOU→BI IQ were hypothesized (IR→BI β = 0.721; PU→BI β = 0.651; PEOU→BI β = 0.495; IQ→BI β = 0.488; p <0.05), then β value predictions, relevant and plausible from the ANN model achieved low, around 129 and 133 prediction error train and test and powered up R^2 prediction value of 0.83. The sensitivity of the predictors, ranked as IR > PEOU > PU > IQ, reveals that the outcomes of the three tiers of Situation Awareness (perception, understanding, projection) indicate that content characterized by low structure, high usability, and substantial, yet poor quality, with enduring post-pandemic usage intentions, was paramount. The contribution of the study includes (i) the first validated hybrid SEM-ANN protocol for education technology acceptance, (ii) proof of the primacy of IR in sustaining BI, and (iii) a pragmatic policy for universities: invest in richer content objects (interactive/multimedia), effortless interfaces, and sustained information governance to maintain engagement even outside of crisis contexts.**

***Keywords:* Technology Acceptance Model, PLS-SEM, Artificial Neural Networks, Information Richness, Information Quality, Behavioural Intention, Online Learning, Post-Pandemic Education**

I. Introduction

Much of the pedagogy conducted using online platforms during the pandemic stimulated new research concerning the adoption of online education systems after the pandemic. With the pandemic, online platforms gained popularity among users for their role in enabling education systems to continue during nationwide lockdowns. This resulted in educational institutions utilizing online systems that varied in their classroom features. As teachers and students, what are the perceptions regarding the online systems in education (Kim et al., 2021; Raza et al., 2021)? Although the pandemic accelerated the adoption of online education systems, the resumption of in-person classes has raised new questions regarding the relevance of online systems (Odilova et al., 2025; Singh & Thurman, 2019).

Substantial research has demonstrated the many advantages of e-learning platforms (Kim et al., 2021; Ayodele et al., 2018; Chayomchai et al., 2020), but almost no research has considered their continued use after resuming in-person classes. More specifically, the concepts of Information Richness (IR) and Situation Awareness (SA), which encompass three levels of perception, understanding, and projection, have not been effectively combined in the usability frameworks that emerged after the pandemic (Saydazimova et al., 2024). In learning, perception relates to the ability to grasp certain information, comprehension refers to the ability to consolidate new knowledge with existing knowledge, and projection pertains to the ability to forecast one's future requirements. These processes determine the effectiveness of mechanisms used in the learning process.

Previous studies categorized these case studies in history according to the types given in the literature, such as the TAM model, Flow theory, and UTAUT model (Esteban-Millat et al., 2018; Al-Maroof et al., 2021), and failed to include the dimensions of IR and SA. The literature has shown that the intentions of students and others are influenced by the constructs of the TAM model and external influences, including enjoyment, innovativeness, and personality (Jeon & Lee, 2025; Saeed Al-Maroof et al., 2020). The role of the IR and Information Quality (IQ) in developing continued behavioral intention still requires further study. Additionally, the widespread adoption of wireless connectivity (Tomei et al., 2024) and the emergence of mobile learning (Kandasamy et al., 2024) have altered the patterns of learners' engagement, necessitating further examination of these factors in the context of the Gulf region following the pandemic.

Methodologically, most prior studies employed single-stage linear SEM (Sohaib et al., 2019), which identifies direct relationships but has difficulties capturing complexity, nonlinearity, and making accurate predictions (Sim et al., 2014). Some efforts integrated ANN but restricted their analyses to shallow architectures with one hidden layer (Bose & Ghosh, 2025; Huang & Stokes, 2016). ANN architectures with multiple layers can capture more profound, nonlinear effects, thereby improving prediction accuracy (Wang et al., 2017). To close these gaps, this study adopts a hybrid deep learning design with SEM–ANN integration to examine TAM constructs alongside IR and IQ in predicting students' behavioural intentions toward online learning platforms.

1.1 Overview of Research Methodology

To investigate students' intentions regarding online platforms, we conducted a literature review and developed a research model. The model, along with four proposed hypotheses intended to model relationships among constructs, is presented in Fig. 1. Students' intention to use platforms is modelled as a function of IR, estimated through constructs of TAM and information quality systems.

1.2 Technology Acceptance Model (TAM)

Administrative computers are certainly one of the most useful online technologies for this demographic. At its core, David's (Davis, 1989)

administration computer TAM technologies are based on models of the computer's perceived usefulness and the necessity to model the system's perceived ease of use. These metrics are the most critical indicators of decision processes and outcomes.

In contrast to TAM, the PEOU is highly beneficial in explaining productivity phenomena and the correlation of processes among the different productive economic agents within the system. Understanding the PEOU phenomenon has been and still is in constant flux for energy and wireless PCs and cellphones. A great deal of evidence from other school-oriented settings, as well as the PEOU PU settings, firmly supports the mentioned phenomena of educational technologies (Chehreh, 2016; McLean & Wilson, 2019).

On these grounds, we propose:

H1: PU predicts BI.

H2: PEOU predicts BI.

1.3 Information Richness (IR)

The elements of IR include precision, relevance, and complexity, which impact IQ (Galdolage, 2021; Yuniar & Fibrianto, 2021) It is associated with user trust and situational awareness (Al-Maroof et al., 2021; Wu et al., 2022). Development in mobile learning and wireless communication (Shen & Prior, 2023) offers advanced situational awareness by providing real-time, context-rich, and multimedia information, which reinforces the SA cycle across perception, understanding, and projection (Saydazimova et al., 2024; Jones & Endsley, 1996). High IR exposure enables learners to process and forecast information optimally, thereby increasing behavioural intention. Hence:

H3: IR predicts BI.

1.4 Information Quality (IQ)

Information IQ is defined as the degree to which information is understandable, impartial, sufficient, and relevant, as stated in (Shan, 2016; Halimeh et al., 2017). High-quality information from Modern wireless and mobile systems (Tomei et al., 2024; Tung & Chang, 2008) facilitates real-time, personalized modification and updates, thus enhancing both accuracy and contextual relevance. Therefore:

H4: IQ predicts BI.

II. Literature Review

Research on the uptake of online education before, during, and after the pandemic has led researchers to conclude that the Technology Acceptance Model (TAM) provides a reasonable assessment of students' behavioral intentions regarding online platforms. (Davis, 1989). Further corroborated in educational settings, learners have a stronger intention to sustain usage of online systems when they perceive online systems to be effort in 'use' performance 'gain' in 'VE' (Jeon & Lee, 2025; Ngampornchai & Adams, 2016). When it comes to TAM models of rich digital media, the acceptance outcomes vary depending on the media's qualities and how users perceive them (Chehreh, 2016; McLean & Wilson, 2019).

Pandemic studies, more than others, have explained the rapid adoption of remote teaching, its ease of use, and the emergence of questions about face-to-face options, which have sustained concerns about usage as the most significant issue (Kim et al., 2021; Raza et al., 2021; Singh & Thurman, 2019). This drives the need to examine the specific information characteristics contained in the platforms to explain the usage over the pandemic period.

2.1 Information Richness (IR) in Digital Learning

The information richness perspective suggests that appropriate, timely, and multi-layered communication minimizes ambiguity and facilitates decision-making, particularly for complex tasks (Shaw et al., 2009; Lo & Lie, 2008). In educational technologies, richer modalities (e.g., interactivity, video, simulations, and collaborative tools) increase engagement and flow, thereby improving acceptance (Chehreh, 2016; McLean & Wilson, 2019). Evidence from other fields shows that IR also enhances trust and perceived value in technology-mediated services (Galdolage, 2021; Wu et al., 2022). During and after COVID-19, enhancements in platform capabilities and instructional design have improved the availability of richer artifacts (e.g., annotated videos, embedded quizzing, adaptive feedback), indicating a plausible IR to BI link. Nonetheless, most post-pandemic adoption studies still center on the broad generalizations of the TAM framework and fail to directly punctuate the role of IR in explaining sustained intention.

2.2 Information Quality (IQ) as a Determinant of Continued Use

The quality of information (QIV), which includes IQ accuracy, completeness, relevance, and clarity, is more important than size when it comes to information systems success (DeLone & McLean, 1992; Seddon & Kiew, 1996; McKinney et al., 2002).

In educational contexts, learners can evaluate the content's credibility, amalgamate the content with the information stored in their prior knowledge, and stay attentive to the course materials because of the high IQ of the content (Shan, 2016; Halimeh et al., 2017; Al-Rahmi et al., 2021; Alturas, 2021). In practice, IQ has been associated with satisfaction and use discontinuance in various digital contexts; however, there has been limited research examining the integration of IQ, IR, and TUM, which explains the use discontinuance in a post-crisis scenario. This presents an opportunity to determine if platforms that are both rich and of high quality retain their BI after the emergency conditions are lifted (Endsley & Garland, 2000; Liu et al., 2009).

2.3 Situation Awareness (SA) as a Theoretical Lens

When it comes to the success of information systems, quality information value (QIV)—which comprises accuracy, completeness, relevance, and clarity—is more essential than size (DeLone & McLean, 1992; Pedrotti & Nistor, 2016; (Seddon & Kiew, 1996; McKinney et al., 2002) Translating e-learning into SA: IR and IQ enhance perception (attending and encoding content cues), comprehension (adding new information to previous knowledge), and projection (forecasting task requirements and future learning). The addition of SA clarifies how IR and IQ relate to sustained intention: richer, higher-quality materials should increase learners' ability to understand and anticipate learning tasks, thus reinforcing BI in a post-pandemic environment.

2.4 From Single-Stage SEM to Hybrid SEM–ANN

Most e-Learning Acceptance studies use single-stage SEM as their primary research method, which validates only linear relationships in the proposed model while ignoring relationships that are nonlinear or are more complex (Sohaib et al., 2019; Sim et al., 2014; Almarzouqi et al., 2022). Hybrid approaches integrate SEM (for causal or theory confirmation) along with artificially constructed neural networks (ANN) (for nonlinear estimation and sensitivity assessment). Prior research on technology acceptance and usage has demonstrated the effectiveness of dual-stage SEM–ANN in enhancing both predictive power and determinant ranking in diverse contexts, such as mobile/wearable services, and social/media behaviors (Sohaib et al., 2019; Bose & Ghosh, 2025; Lee et al., 2020; Alhumaid et al., 2021; Leong et al., 2019). Following this line of reasoning, with smooth hybrid ANN architectures (several hidden layers), neural networks are expected to capture sophisticated patterns better than shallow, single-hidden-layer models (Huang & Stokes, 2016; Wang et al., 2017). A hybrid model is beneficial in this case, as it optimally combines proof (TAM with IR/IQ) and predictive goals, offering the best of both worlds in addressing the continued BI gap.

2.5 Post-Pandemic and Mobile-First Context

The on-campus learning in the post-pandemic period aligns with the mobile-first trend and improvements in wireless adoption, allowing for anytime, anywhere access to microlearning and adaptable delivery elements that can enhance their richness and quality.

Such advancing ecosystems remind us of the need to empirically revalidate the acceptance models with focused information variables and contemporary delivery opportunities.

2.6 Synthesis and Research Positioning

Previous literature reconizes (i) TAM is more reliable when predicting e-learning adoption (ii) importance more conceptually then in application IR and IQ's joint modeling in post-pandemic continuation (iii) alomost completely neglected by SA the cognitive path to BI framing it in www information to make it more structured (iv) the improvement in methodology from hybrid SEM ANN commpared to single stage SEM in determining nonlinear relationships with (Sohaib et al., 2019; Bose & Ghosh, 2025; Lee et al., 2020; Alhumaid et al., 2021; Leong et al., 2019). To fill these gaps and tackle the challenges, this work employs a dual-stage SEM-Deep ANN to verify and refine the TAM-IR-IQ-SA model.

III. METHODOLOGY

Hypotheses 1 and 2 about the platform's utility and simplicity of use, as well as Hypotheses 3 and 4 about the information richness and quality, are captured by the model.

These constructs are aligned with the Situational Awareness theory framework, placing the discerning, comprehending, and projecting cognitive steps associated with these information attributes to enduring behavioral intention. There are four hypotheses, which have been set H1 to H4, to capture these constructs. These are shown in Fig. 1.

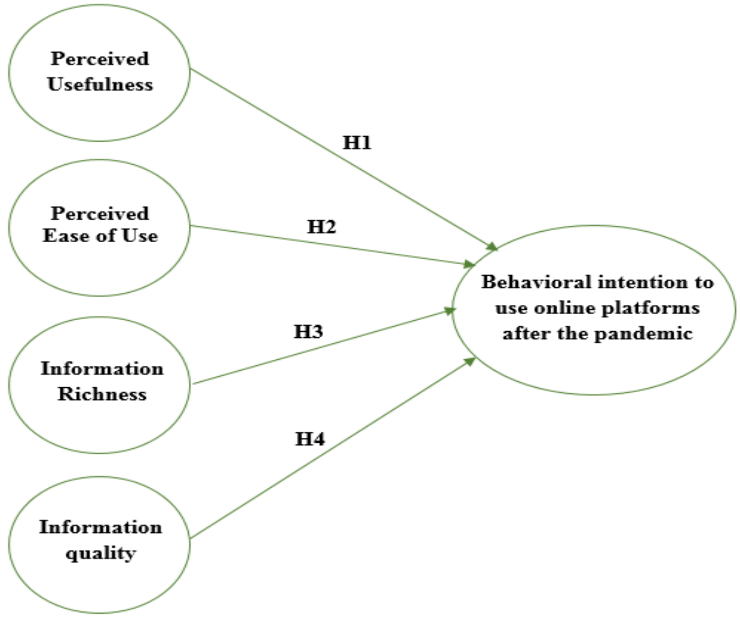

Fig. 1 Proposed Research Model

3.1 Data Collection and Sampling

The research for this study used a cross-sectional survey design and ran from October 25, 2021, to December 25, 2021.

Seven hundred questionnaires were distributed to students in colleges in the UAE, and 683 responses were returned, which corresponds to a 91% response rate. Out of the 683 responses, 638 were deemed legitimate after the screening and were used in the analysis. Three hundred six responses were considered the minimum sample requirement for a population of 1,500 students (Krejcie & Daryle, 1970). Therefore, the sample size of the study was deemed sufficient for the purposes of conducting structural equation modelling (SEM) (Chuan & Penyelidikan, 2006). Purposeful sampling, as outlined by Al-Emran and Salloum (Al-Emran & Salloum, 2017), was employed in this study, ensuring that participants were only students with prior exposure to online learning.

3.2 Respondent Demographics

There were 59% male respondents and 41% female respondents. Most (72%) were aged 18–29, while the rest were 29 years or older. With respect to educational qualifications, 65% held a bachelor's degree, 18% a master's degree, and 17% a doctorate. Participants were drawn from various programs and institutions across the UAE, which improved the generalizability of the outcomes. The demographic information was examined using IBM SPSS Statistics to obtain basic descriptive information and corroborate the representativeness of the sample.

3.3 Measurement Model

Using relevant empirical studies adapted from the TAM and information systems literature and validated scales, we defined and contextualized the various dimensions of perceived system sophistication, usability, and usefulness, as well as the information's richness and quality and the user's behavioral intention (Davis, 1989), (Chehreh, 2016; Halimeh et al., 2017). A five-point Likert scale was used for all questions, with 1 indicating severe disagreement and 5 indicating strong agreement. Employing the given criteria of approved thresholds, we utilized Cronbach's composite reliability (CR), Dijkstra-Henseler's rho A (ρA), and average variance extracted (AVE) to evaluate reliability and validity (Hair, 2011; Hair Jr et al., 2021).

3.4 Analytical Strategy

Methods such as Structural Equation Modelling and Artificial Neural Networks were utilized in a two-stage hybrid approach. Utilizing the structural equation modeling PLS techniques and the best practices of the information systems field, this initial step was accomplished using the software SmartPLS 3.0 (Ringle et al., 2015). The field's guidelines (Al-Emran et al., 2018) outline a methodical evaluation and individual improvement of the measurement and structural models (Simpson, 1990). Factor loadings, the AVE, the Fornell-Larcker criterion, and the heterotrait-monotrait ratio of HTMT were used to determine convergent and discriminant validity (Hair et al., 2017; Voorhees et al., 2016). Bootstrapping methods were used to evaluate the structural model to assess the postulated model (Hair Jr et al., 2021; Chin, 1998).

In stage two, ANN analysis was conducted to identify nonlinear relationships and determine predictor ranks. As in previous SEM–ANN applications, MLP architecture was employed with two hidden layers (Sohaib et al., 2019; Bose & Ghosh, 2025; Lee et al., 2020; Alhumaid et al., 2021; Leong et al., 2019). Input variables were PU, PEOU, IR, and IQ, and the output node was set to BI. The neural network was trained with appropriate normalized input data and sigmoid activation functions, and ten-fold cross-validation was used to mitigate overfitting (Glorot & Bengio, 2010; Kohavi, 1995). Overfitting was assessed using RMSE and predictive R^2.

IV. Findings and Discussion

4.1 Data Analysis

This particular research employed a mixed approach, utilizing SEM and ANN methodologies to test and validate the research model. In the first stage, Partial Least Squares-based Structural Equation Modeling (PLS-SEM) was executed using the SmartPLS software (Ringle et al., 2015) and as per the guidelines of (Al-Emran et al., 2018). In accordance with the literature, and as described in best practices, the two-step procedure of a measurement model assessment and a structural model evaluation was utilized in determining the validity and reliability of the constructs as a prerequisite to testing hypothesized relationships (Simpson, 1990).

The group, which we refer to as the second stage of the two-stage approach conducted in this study, utilized artificial neural networks to capture nonlinear patterns and enhance prediction accuracy. For this purpose, we used a multilayer perceptron (MLP) because it has been proven to be highly useful in classification and regression tasks (Sohaib et al., 2019; Bose & Ghosh, 2025). The input layer had neurons corresponding to independent variables (PU, PEOU, IR, and IQ), and the output layer had one neuron corresponding to behavioral intention (BI). The model was trained with nonlinear activation functions, which helped in solving the complex interactions beyond simple linear relationships in the data when using SEM, particularly in cases with complex interactions in the data. The model was also cross-validated using a ten-fold procedure to minimize overfitting. This two-stage approach offered both theoretical validation through SEM and predictive strength through ANN, which provided the confidence that both the statistical significance and the practical accuracy in modeling students' behavioral intentions toward online learning platforms were achieved.

4.2 Convergent Validity

The reliability and validity of the measurement model were examined using composite reliability (CR), Dijkstra-Henseler's rho A (ρA), Cronbach's alpha (CA), and specific convergent validity metrics (Table I and Table II).

In this model, the outcome of CA as presented in Table III and Table IV ranged from 0.799 to 0.871, which meant all of them were above the required benchmark of 0.70 and thus confirmed internal consistency (Nunnally & Bernstein, 1994; Henseler et al., 2016). In the same model, the CR, which is benchmarked to 0.70, ranged from 0.800 to 0.886 [44]. Also, the ρA coefficients in the model, which are indicated to be above 0.70, provide construct reliability with the prevailing accepted evidence as outlined in (Dijkstra & Henseler, 2015; Hair Jr et al., 2021).

The average variance extracted (AVE) and factor loadings were used to cross-validate the convergent validity between the constructs. Validating that each construct explained more than half of the variation of its indicators, with AVE values ranging from 0.547 to 0.790, which is over the minimum requirement of 0.50 (Lee et al., 2020).

The results provided in this section further suggest that the constructs are not only average reliable but they are also boundary reliable and convergent valid, which further proves the measurement to be enduring. The model in the following section can be confidently relied on.

4.3 Discriminant Validity

For a model to be discriminantly valid, each of its constructs must be sufficiently different from one another to warrant empirical separation. The Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio were two well-established metrics in this regard (Hair et al., 2017). Because the square root of the AVE for each construct was larger than, and thus beyond, the correlations to the other constructs, Table V confirms appropriate discriminant validity and satisfies the Fornell-Larcker criterion (Hair Jr et al., 2021; Fornell & Larcker, 1981; Sarstedt et al., 2021).

In the same manner, HTMT analysis (Table VI) showed that all construct pairs were below the conservative boundary of 0.85, which set forth that there was an absence of multicollinearity, thereby proving each construct is measured separately (Dijkstra & Henseler, 2015; Henseler et al., 2015; Voorhees et al., 2016). The results show that the measurement model has good discriminant validity. The results provide significant support for the robust measurement model, which allows for the confident assessment of the structural model (Henseler et al., 2016; Hair et al., 2017). This model has also demonstrated reliability and convergent validity.

4.4 Hypotheses Testing Using PLS-SEM

The significance of the hypothesized links in the structural model was determined using bootstrapping in the PLS-SEM analysis within SmartPLS. (citation xx, citation xx). The model assessed indicated that BI explained 63.2% of the variance in behavioral intention. The BI model had a substantial explained variance. (citation xx). Table VI and Fig. 2 show the standardized path coefficient (β) estimates, t, and p values.

Unconditionally, all four hypotheses (H1 - H4) were confirmed. Users who had high perceived usefulness were shown to have high BI ($\beta = 0.651$, $p < 0.001$), and BIs were positively influenced by perceived ease of use (PEOU) ($\beta = 0.495$, $p < 0.001$). Emphasizing information richness (IR), users had the highest information behavior intention (BI) ($\beta = 0.721$, $p < 0.001$), followed by those with high information quality (IQ) ($\beta = 0.488$, $p < 0.05$).

TABLE I ANALYSIS OF CONVERGENT VALIDITY

Const	Items	Loading factors	Cronbach's Alpha	CR	PA	AVE
BI	BI1	0.898	0.833	0.886	0.885	0.598
	BI1	0.847				
IQ	IQ1	0.859	0.865	0.861	0.860	0.790
	IQ2	0.887				
	IQ3	0.821				
IR	IR1	0.861	0.871	0.801	0.821	0.641
	IR2	0.850				
	IR3	0.884				
PEOU	PEOU1	0.799	0.799	0.800	0.805	0.547
	PEOU2	0.763				
	PEOU3	0.851				
PU	PU1	0.801	0.855	0.867	0.868	0.700
	PU2	0.848				
	PU3	0.754				

TABLE II ANALYSIS OF FORNELL-LARCKER SCALE

	BI	IQ	IR	PEOU	PU
BI	**0.890**				
IQ	0.502	**0.802**			
IR	0.535	0.385	**0.815**		
PEOU	0.625	0.559	0.556	**0.896**	
PU	0.678	0.390	0.535	0.428	**0.891**

TABLE III ANALYSIS OF HTMT

	BI	IQ	IR	PEOU	PU
BI					
IQ	0.413				
IR	0.572	0.528			
PEOU	0.628	0.619	0.148		
PU	0.625	0.369	0.441	0.531	

The results reinforce the assertion that the old TAM model information and new information attributes of the system (IR and IQ), along with PU and PEOU, have a critical influence on the adoption of online platforms in the post-COVID-19 world. Most strikingly, information richness stood out above all other predictors of post intention for use behavior in mobile and online learning, highlighting the centrality of content richness in behavioral intention (Table V).

TABLE IV R2 ANALYSIS

Constructs	R2	Findings
BI	0.632	Moderate

TABLE V HYPOTHESIS TESTING ANALYSIS

H	Proposed relationship	Path	t-value	p-value	Supported
H1	PU -> BI	0.651	11.581**	0.000	Yes
H2	PEOU -> BI	0.495	13.230**	0.000	Yes
H3	IR -> BI	0.721	15.622**	0.000	Yes
H4	IQ -> BI	0.488	4.328*	0.020	Yes

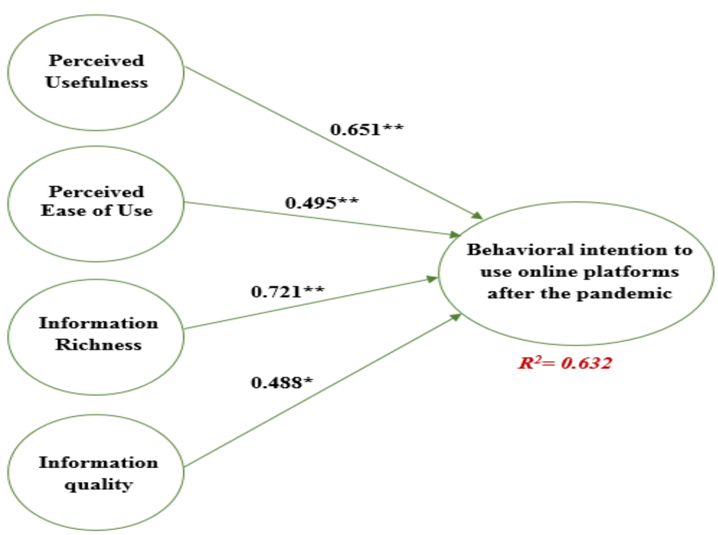

Fig 2. The Structural Model

A two-hidden-layer deep ANN, as recommended by deep learning frameworks, was used to improve learning capacity and capture intricate relationships. The hidden and output layers use nonlinear transformations, such as sigmoid activation, to improve the accuracy of the output prediction. Following the recommendations of best practices in neural network modeling, we normalized the input and output data to the range of 0 and 1 to improve model convergence and performance. We implemented a tenfold cross-validation with an 80:20 train-test split to assess model stability and reduce the risk of overfitting. The training set RMSE was 0.1285, and the testing set was 0.1329, which indicates model accuracy.

The differences in standard deviation of 0.0047 during training and 0.0093 during testing can be considered minimal and thus indicative of stable performance. These further underscores the ANN model's impressive capability of predicting behavioural intention (Fig.3).

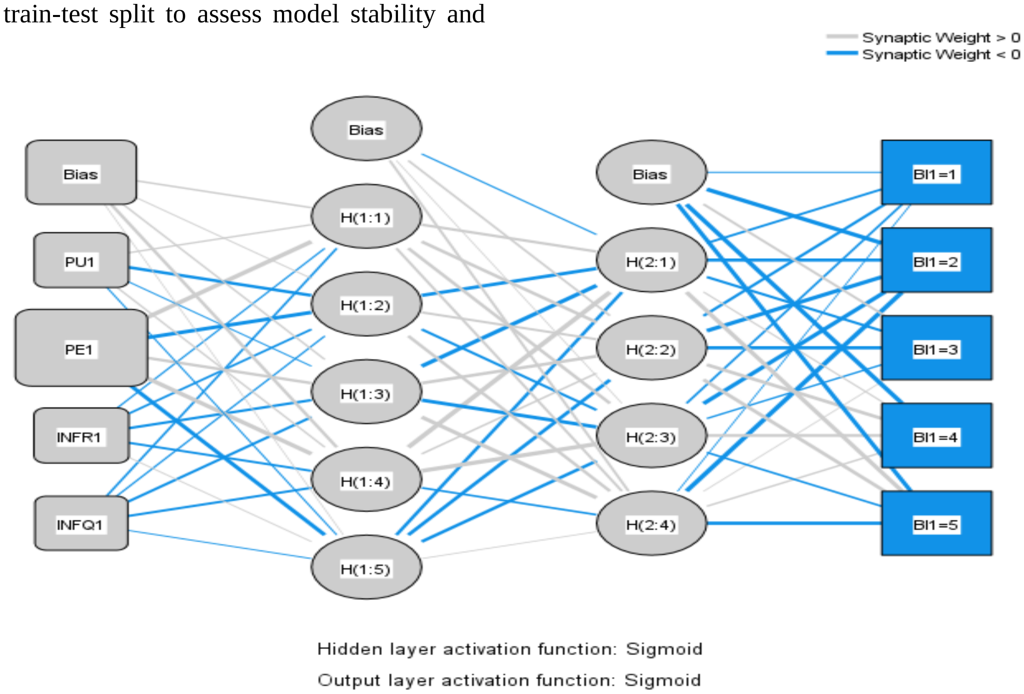

Fig. 3 ANN Model

4.6 Sensitivity Analysis

The allocation of importance is completed through a sensitivity analysis, which measures the average impact of each input variable by focusing on the most critical one. According to Table VI, the strongest predictor of behavioral intention is IR, followed by PEOU, PU, and IQ in that order. This order of arrangement shows the variable hierarchy of the ANN model. Both PLS-SEM and ANN offer methods to evaluate structural analysis, and each has its own set of benefits; model fit evaluation is a good way to find out how well an ANN model holds up and how accurate its predictions are. In this instance, the predictive capability of the ANN is greater. In this instance, ANN produced an R^2 of 83% which is substantially greater than the 63.2% explained variance that was calculated through PLS-SEM. This data demonstrates that the ANN is better placed to capture the complex, cross-nonlinear relationships among constructs often ignored in linear SEM techniques. Even in the absence of a single, cohesive approach, both models corroborate the importance of the constructs that influence behavioral intention. Within the complex linear and nonlinear dependency sequences, the underlying reason is the sophisticated learning capabilities of the ANN, which facilitate greater access to concealed structures and complex interdependencies.

TABLE VI INDEPENDENT VARIABLE IMPORTANCE

	Importance	**Normalized Importance**
PU	.101	14.2%
PEOU	.109	15.4%
IR	.711	100.0%
IQ	.079	11.1%

V. Discussions

Students' behavioral intentions to continue using the online learning system after the pandemic were influenced by the TAM model (PU, PEOU) and information attributes (IR, IQ), as confirmed by the analysis, which also highlighted the joint construct value of the four hypotheses.

The findings reveal three significant insights.

First, information richness (IR) was the strongest predictor of BI. This aligns with Situation Awareness theory, which posits that a user's perception, comprehension, and projection synergistically enhance their ability to tackle and anticipate complex learning tasks (Saydazimova et al., 2024; Jones & Endsley, 1996). The presence of interactive content, real-time feedback, and varied multimedia resources consolidated students' engagement, demonstrating that content-rich platforms enable more sustainable adoption.

Second, PEOU and PU still hold significant importance. PEOU illustrates learners' preference for tools that streamline and facilitate the learning process, while PU emphasizes the advantages of online systems in enhancing teaching. Their observations are consistent with previous TAM-based research, which affirms the importance of these constructs in the adoption of technology in education (Jeon & Lee, 2025; Ngampornchai & Adams, 2016; (Chehreh, 2016; McLean & Wilson, 2019). Collectively, they underscore that post-pandemic technology acceptance still hinges on its use and usefulness.

Third, the quality of information (IQ) also had a significant positive influence on BI, confirming that Biased, incomplete, or outdated content does not favor the perception of online content learning portals. This is supported by previous literature on the impact of IQ on the use and satisfaction of a technology (Effendy et al., 2021; Al-Rahmi et al., 2021). These results also corroborate the existing literature, which suggests that higher IQs enhance user trust and the effectiveness of users in digital learning environments (DeLone & McLean, 1992; Alturas, 2021; McKinney et al., 2002).

In conclusion, the original findings suggest that TAM is modified by incorporating IR and IQ, within the framework of SA, to account for continued use even after the pandemic. This work advances the theory to the extent that the information characteristics in the proposed model are as imperative as the traditional TAM components, and also to the extent that practical implications stem from the work, in the sense that educational institutions must focus on systems that integrate high-quality, reliable content with a rich multimedia design.

VI. Conclusion and Future Work

This study employs a two-stage SEM-ANN approach to integrate analysis, focusing on the use of online learning platforms in the post-pandemic era, and examines the specific nature of TAM in relation to the envelope's information richness and information quality. The results showed that all four predictors influenced behavioural intentions, with IR being the strongest predictor, and PU, PEOU, and IQ trailing. Aspects of TAM adapted to account for the importance of the attributes of information, which, as explained through the situation awareness theory, are critical for sustaining the adoption of online learning in non-crisis situations. From the perspective of the practice, the research highlights the importance of universities investing in interfaces that blend high-quality and usable, information-rich, multimedia content.

Even with these contributions, there are still many limitations. First, the attempt had to be restricted to students from the Gulf region, i.e., the scope of the results is limited to this region. The study design is cross-sectional, and therefore, it lacks temporal insights; capturing developing adoption patterns requires longitudinal data. Finally, closed-ended self-reported surveys may introduce response bias into the data.

With the aid of these insights, further research could expand the study scope to other regions and cultures (e.g., Asia, Europe) and incorporate additional elements to broaden the framework around technology acceptance. The use of qualitative research techniques, such as interviews and observations, could contribute more to understanding the learners' experiences with the online system.

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