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5G Adoption Modeling in the Gulf: A Deep Learning–Driven SEM Framework for Intelligent and Dependable Wireless Networks

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Abstract

The research aims to adopt 5G services in Gulf countries with an SEM-ANN approach. 5G services are gauged with a modified Technology Acceptance Model (TAM) with Perceived Skill Readiness and Perceived Resources constructions to comprehend infrastructure and user competence. Four hundred eighty-five participants (January-February 2022) were examined in the PLS-SEM approach to validate the measurement and structural relationships (R^2 for behavioral intention = 0.476). A trained two-hidden-layer multilayer perceptron ANN was used after PLS-SEM to account for nonlinear relations and increase predictive accuracy (ANN $R^2 \approx 0.80$). IPMA and sensitivity ranking show that the most important aspects of 5G adoption are Perceived Enjoyment and Perceived Resources. This work conceptually expands the TAM with Infrastructure and Skill Readiness and Methodologically with SEM-ANN hybrid and IPMA metrics. Focus on user-centered experience design and infrastructure readiness are the derived recommendations for management to increase the 5G network reliability. Future research directions are discussed.

Keywords: 5G Adoption, SEM–ANN Hybrid, Importance Performance Map Analysis, Perceived Enjoyment, Perceived Resources.

1 Introduction

Fifth-generation (5G) technology is revolutionizing the mobile ecosystem with ultra-low latency, high data rates, and energy efficiency, along with massive connectivity features, all of which are pertinent to realizing the promise of secure applications (Gao, 2021). They are not 4G upgrades; they are the characteristic pillars of next-generation mobile ecosystems such as smart e-Cities, new medicine, and immersive real-time collaboration (Baratè et al., 2019). 5G also offers consciousness of the surrounding environment together with ultra-wideband communication, the building blocks of the next-generation smart (Song et al., 2025).

In the era of omnipresence of 5G technology, it challenges users with high mobility in terms of location and the applications they utilize. The challenges have completely reshaped how users experience every industry. Particularly, 5G in education and universities is considered a live-streaming

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video communication platform and a real-time data exchange platform between instructors and students (Ahad et al., 2020). Moreover, 5G technology enhances the development of virtual and augmented reality, as well as deep learning frameworks (Kim et al., 2020). The outcomes of learning these frameworks are enhanced with a reduction in delays and high-speed data transmission capabilities provided by 5G technology (Shao et al., 2020). The 5G system is also being developed within the healthcare sector, as the technology aims to usher in affordable, practical, and intelligent systems based on fast and reliable data transmission (Peng et al., 2020).

The Gulf region offers excellent potential for investigating 5G adoption due to its ambitious digital transformation undertakings. However, the impact of user behavior on the dependable functionality of wireless systems has received minimal attention in the existing literature, which primarily focuses on infrastructure deployment or service provisioning (Ofoghi, 2015; Alrusaini, 2025; Al-Maroof et al., 2021). While the technology acceptance model (TAM), along with structural equation modeling (SEM), has provided fruitful theoretical constructs, the mobile intelligent network appears to be an area where irrational changes (Han & Zhang, 2020; John et al., 2024) have not been adequately addressed within these frameworks. A good example is the tourism industry, which has been very agile in responding to the entire epidemic by creating innovative digital 5G-based tourism products (Senthil et al., 2025).

The epidemic accelerated the 5G digital interaction beyond the journey, especially on Instagram, TikTok, and YouTube, where consumers embraced user-generated content and rapid internet (Mustafa et al., 2022; Sohaib et al., 2019), particularly with the 5G network. Similar trends prevail in both military and agriculture. In terms of 5G agriculture, for example, the new virtual reality and the infrastructure of robotics are allowed to be implemented in agriculture, which enables an increase in operational accuracy and general efficiency advantage (Han et al., 2024). As suggested in new research, 5G uptake continues to rely on TAM factors such as perceived utility (PU) and perceived easily of use (PEOU) (Saflor et al., 2024). Adopting the Technology Acceptance Model (TAM) has proven effective in assessing users' behavioral tendencies, particularly in terms of value and ease of technical evaluation. Several scholars (Kala & Chaubey, 2024) have made advances in TAM by adding some attributes that shape users' sentiments towards wireless technology adoption (Al-Emran et al., 2021), such as computer anxiety, self-efficacy, past experiences, and social norms (Ilieva et al., 2024). Even so, the described approaches are fundamentally unidirectionally focused in their conclusion and mostly simplistic data analysis processes (Ilieva et al., 2024). The same holds for the approaches of SEM (Kiat et al., 2025), which remain rudimentary as aids for prediction in decision-making processes, as they are used to model complex systems with nonlinear correlations (Wu & Yu, 2025).

Research Contribution

1. Capturing the linear and nonlinear determinants of 5G adoption through the SEM-ANN Hybrid model intelligent modeling.
2. Integrating user competence and infrastructure latency behavioral constructs for robust 5G systems.
3. Applying IPMA to the strategic analysis of the scalable and context-aware deployment of 5G.
4. Delivering empirical evidence to assist policymakers and network builders in facilitating reliable wireless access.

The research is structured as follows: Section 2 expands on the literature regarding the adoption of 5G services in specific areas, alongside dependable network applications, and the application of these networks. Then, in Section 3, I give a context analysis of the hypothesis model I am presenting. In

Section 4, I describe in detail the research analysis plan, which includes the evaluation of a deep learning model, as well as the assessment of the model itself. Then, in Section 5, I present the results. From there, Section 6 is dedicated to discussing the results and findings, as well as providing a final summary that includes limitations and future work.

2 Literature Survey

The literature available on 5G adoption is divided into two streams: behavior studies and technical adaptation. Technical adaptation focuses on system issues such as offloading, edge computing, spectrum management, and adaptation of QOS (Q. Hugh & Freddy Soria, 2025). To enhance network performance in terms of reliability, delay, and throughput, solutions such as hyper-scale-based blockchain orchestration, reinforcement learning, and dynamic network slicing have been proposed. They creatively carry forward the engineering of the 5G system optimally, but overlook massive behavior and perception without considering user dimensions, which are equally important in presenting the reality of 5G.

The second section addresses the acceptance and behavior modeling problem that typically accompanies the integrated theory (UTAUT) and structural equation modeling (SEM) of the Technology Acceptance Model (TAM), specifically in the context of acceptance and technology use. Earlier studies classify adoption drivers as perceived utility (PU) and reduced ease of use (PEOU), but the measurement is primarily done through a single-phase, linear model.

These models do not accurately capture the advanced, nonlinear interactions that characterize complex user decision-making in emerging wireless services. For example, skills have rarely been studied in terms of 5G uttech, led by user-led constructions such as readiness, perceived pleasure, and resources (Perry, ENJ, and Race). Later research has begun to examine hybrid approaches to achieve better articulation of more forecasting power and nonlinear relationships than combining SEMs with ANN.

These tend not to consider large, established 5G markets and focus on more niche areas (e.g., m-health, mobile payments). A few of these include priority strategies, such as IPMA, being considered within the analysis, so that the output can be utilized to provide actionable advice to network operators and policymakers.

Table 1 presents representative works from these two streams of angling, including methods, contributions, and their respective drawbacks. The literature certainly builds a substantive grounding, but the gaps highlighted in this table are critical.

(i) restricted nonlinear behavioural interdependency modelling,

(ii) a user-facing readiness and infrastructure correlates imbalance, and

(iii) actionable insights regarding prioritization for the strategic framework

These gaps help explain the absence of a predictive, user-centered model combining behavioral and infrastructure determinants, nonlinear adoption dynamics, and actionable recommendations for network providers and policymakers.

Table 1: Representative studies on 5G technical and behavioral research

Authors	Focus Area	Methods Used	5G Relevance	Contribution Type	Limitation
Sellami et al., 2022	Energy-aware task offloading in SDN-Blockchain-IoT	Deep Reinforcement Learning	Edge computing & network optimization	Technical Framework	Limited focus on user behavior and adoption intent
Quasim, et al. 2025	Resource management in smart edge computing	Blockchain + Deep Learning	5G heterogeneous networks	Intelligent System Design	No integration of behavioral or decision models
Sharma & Sharma, 2019	Mobile banking trust & quality factors	Empirical (SEM)	Indirect (Mobile Services)	Behavioral Trust Modeling	Outdated; not specific to 5G or current mobile infrastructure
Asadi et al., 2019	Wearable healthcare device adoption	SEM + ANN Hybrid	IoT/Healthcare integration	Predictive Behavioral Model	Narrow domain (healthcare wearables); lacks network dependency
Lee et al., 2020	Wearable payments adoption	Dual-stage SEM-ANN	Smart payment over mobile	Deep Learning Behavioral Insight	Limited application to wireless network reliability
Leong et al., 2019	Social media addiction study	SEM + Neural Network	Indirect (Mobile behavior)	Hybrid Psychological Modeling	Does not consider infrastructural readiness or 5G impact
Maeng et al. 2020	Forecasting 5G service demand	Econometric forecasting	Direct (5G market dynamics)	Market Behavior Analysis	Ignores user-level behavioral predictors and nonlinearity
Dadhich et al., 2023	5G adoption by new-age users	TAM + UTAUT + PLS-SEM	Direct (5G behavior in emerging markets)	Multi-stage User Behavior Modeling	Lacks ANN integration for nonlinear insights
Oyeniran et al., 2023	5 G's impact on software engineering	Analytical review	5G effect on mobile apps	Software Engineering Implications	Conceptual; lacks empirical or predictive validation
Pethuraj et al., 2023	Quality of service in 5G for E-commerce	Optimized data techniques	Direct (5G communication analysis)	Quality of Service Optimization in Applications	Does not account for behavioral adoption factors

3 Hypotheses Development and Conceptual Model

To comprehend why a particular population adopts a new technology like 5G requires not only cognitive and affective factors, but also structural factors, of which dependable and intelligent mobile network systems are a part. The Technology Acceptance Model (TAM) has been, and continues to be, utilized to interpret user adoption behavior. However, in this instance, the TAM framework is being enhanced by adding three more constructs: Perceived Skill Readiness (PERI), Perceived Enjoyment (ENJ), and Perceived Resources (RES), which are deemed critical in pervasive computing environments (Hoo et al., 2024). Collectively, these constructs capture the behavioral, experiential, and infrastructural factors required to support dependable and contextually aware 5G services.

Perceived Skill Readiness (PERI)

PERI illustrates the adoption readiness and confidence users have toward mobile and ubiquitous computing technologies (Himawan et al., 2025). User competency is critical and perceptively advanced in self-rated technological proficiency toward 5G-enabled services in 5G-enabled telemedicine and industrial IoT contexts due to their real-time engagement and remote-control system dependency.

H1: PERI has a significant positive impact on intention to use 5G.

Technology Acceptance Model (TAM)

The TAM framework outlines users' behaviors and attitudes towards technology based on two factors: Perceived Usefulness and Perceived Ease of Use (PEOU) (Hassan et al., 2024). In the case of 5G, innovative tools such as smart classrooms and live traffic control systems, the ease of use positively affects both trust and the system's uptake (Jang & Kim, 2024). In this research, PEOU and PU are considered primary factors within a network of other factors that together influence the adoption of 5G technology.

H2: PU has a significant positive impact on intention to use 5G.

H3: PEOU has a significant positive impact on intention to use 5G.

Perceived Enjoyment (ENJ)

Enjoyable technology involves self-contained pleasure and engagement, which deepens pleasure value. Users relate enjoyment to 5G because of the augmentation of enjoyment brought about through the use of AR/VR devices, as well as gamified learning, which are complemented by 5G networks in the immersive and low-latency context (Ahmad et al., 2021). The perceived value enjoyment extends the period of use and increases trust in the system. It has been suggested that the amount of enjoyment considered by students in undergraduate programs in Saudi Arabia is minimal (Xu et al., 2019). However, pervading evidence from Malaysia is that enjoyment is a pivotal factor in accepting and being ready for technology.

H4: ENJ has a significant positive impact on intention to use 5G.

Perceived Resources (RES)

RES captures user perception regarding technical and organizational support infrastructure, bandwidth, devices, and organizational support for 5G use, as well as their attendant support. In mobile environments, dependable infrastructure is a critical requirement for reliable 5G operations (Antoniewicz & Dreyfus, 2024; Mahadevan et al., 2025). Previous studies have indicated that resource availability creates user and technology new adoption intention. In addition, RES is assumed to be a derivative of the TAM's central components, PU and PEOU, and proprietary in the formulation of user adoption.

H5: RES has a significant positive effect on intention to use 5G.

Conceptual Model

Based on the above hypotheses, a conceptual model was developed (Figure 1) to examine how PERI, PU, PEOU, ENJ, and RES jointly influence users' intention to adopt 5G technologies in the Gulf context.

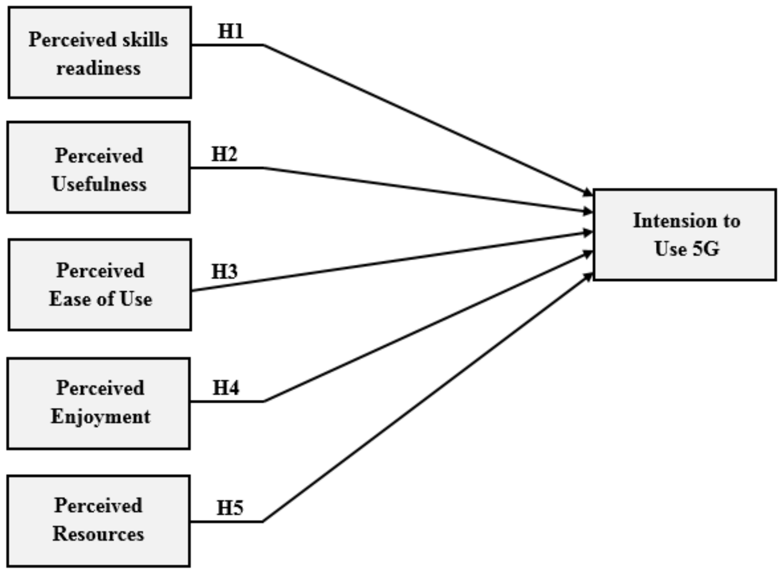

Figure 1: Hypothesis model

4 Research Analysis

This research combines Structural Equation Modeling (SEM) and Artificial Neural Networks (ANN) techniques to assess the behavioral intention regarding the use of 5G technology in the Gulf region. The model combines predictors of a psychological nature (PERI, ENJ, PU, PEOU) with an infrastructural one (RES) to address the ordinal and cardinal influences of user decisions on intelligent wireless networks (Thooyamani et al., 2014). The model's validation and causality analysis were based on the use of SEM, while the ANN's role was to identify elaborate and non-compensatory frameworks that were overlooked by classical correlation techniques. Additionally, Importance–Performance Map Analysis (IPMA) and sensitivity analysis of key constructs were used to supportably and contextually prioritize 5G technology deployment, proving to be vital and dependable.

4.1 Data Collection and Participants

It was collected using pre-designed questionnaires that made use of the TAM model. Questionnaires were administered to 500 customers of the university and Gulf region technology centers in the winter trimester of the academic year (January-February 2022). Based on the completed responses, a total of 485 samples were gathered (response rate: 97%), which definitely surpasses the suggested SEM sample threshold limits for ubiquitous computing environments. Respondents exhibited a range of diversity in their Gender (59% male and 41% female), age (67% with ages between 18 and 29), and level of education (66% bachelor's, 20% master's, and 14% doctoral), thus demonstrating broad generalizability with respect to user population demographics (Antonov et al., 2025; Pethuraj et al., 2023). A purposive sampling technique was used as suggested for studies based on voluntary participation in mobile service studies (Pethuraj et al., 2023).

Algorithm 1: 5G Adoption Modeling Using SEM-ANN and IPMA

Input: Data on survey with constructs $PERI, PU, PEOU, ENJ, RES, INT5G$

Output: Result: Valid (1) or Invalid (0)

1. Initialize Prepare data on Pop with survey with constructs: $PERI, PU, PEOU, ENJ, RES, INT5G$.
2. While $gen < max\_gen$ do
3. Data Collection
   - Use pre-programmed questionnaires, derived on the basis of Technology Acceptance Model (TAM) to gather survey data on constructs: $PERI, PU, PEOU, ENJ, RES, INT5G$.
4. End procedure
5. SEM Modeling
   - Define the SEM model relationships:

$$INT5G = \beta_1 \times PERI + \beta_2 \times PU + \beta_3 \times PEOU + \beta_4 \times ENJ + \beta_5 \times RES + \epsilon$$

Use PLS-SEM to estimate path coefficients $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$and validate the model fit with SRMR and NFI.

6. End procedure
7. ANN Modeling
   - Prepare input data using constructs $PERI, PU, PEOU, ENJ, RES$and output $INT5G$.
   - Establish the architecture of ANN model in two hidden layers and Sigmoid activation.
   - Cross-validate (10-fold) the model and calculate the performance metrics of RMSE and R-squared
8. End procedure
9. Sensitivity Analysis
   - Using ANN sensitivity analysis analyze the significance of predictors and normalize the score of importance.
   - Rank predictors according their relative value of adoption of 5G.
10. End procedure
11. IPMA (Importance-Performance Map Analysis)
    - Calculate the Importance of each construct based on path coefficients from SEM.
    - Calculate Performance by computing the mean value for each construct.
    - Generate the IPMA map with Importance on the x-axis and Performance on the y-axis.
    - Identify constructs with high Importance but low Performance for strategic focus.
12. End procedure
13. Interpretation and Recommendations
    - Analyze findings to establish the most notable variables influencing the 5G adoption.

- Provide actionable recommendations to improve adoption based on IPMA and ANN analysis.
- End procedure
- End while
- Output the final result: Valid (1) or Invalid (0).

The 5G adoption modeling based on SEM-ANN and IPMA in the form of algorithm 1 begins with the process of data collection as the TAM-based surveys aimed at such constructs as PERI and PU. The modeling of relationships and the validation of the fit are done by PLS-SEM. Subsequently, a two-layers ANN is trained to ensure the presence of non-linear relations and prediction validation. Sensitivity analysis prioritizes the constructs in terms of their effect on the adoption of 5G and IPMA produces a map where the improvements are ranked by their importance and performance. Lastly, interpretation and recommendations give a practical understanding of improving the adoption of 5G.

4.2 Measurement Instrument and Pilot Testing

The instrument captured six constructs: PERI, PU, PEOU, ENJ, RES, and Intention to Use 5G (INT5G), which were individually operationalized and measured using multi-item Likert-type scales based on the extant TAM literature. Cronbach's alpha reliability estimates were calculated using SPSS for the 50 students (10% of the main sample) included in the pilot study. All constructs exceeded the 0.70 threshold (Table 2), and so there is internal consistency. Moreover, the primary research evaluated convergent validity (mean AVE extracted > 0.5), discriminant validity (HTMT < 0.85), and composite reliability (CR > 0.7) to provide evidence of psychometric robustness.

Table 2: Cronbach’s internal reliability

Constructs	Cronbach’s α
INT5G	0.741
PERI	0.883
PEOU	0.766
PU	0.849
ENJ	0.914
RES	0.728

PERI (0.883) and ENJ (0.914) demonstrated excellent reliability, while RES (0.728) and INT5G (0.741) met the minimum threshold, confirming that the items are suitable for behavioural modelling in 5G contexts.

4.3 SEM Modelling

The structural model and the associated path coefficients were estimated by carrying out the PLS-SEM analysis using SmartPLS software. This approach was selected due to its performance on small and moderate sample sizes and lack of normality in the data distribution, which is typical in networked systems. Model fit was assessed with the following cutoff indices: SRMR < 0.08 and NFI > 0.90. The significance of the hypothesized paths, as well as many of the key direct and indirect effects of the constructs, was analyzed using 5,000 resamples of the bootstrap method.

SEM Model

SEM model represents the connections between constructs (Perceived Skill Readiness- PERI, Perceived Usefulness- PU, Perceived Ease of Use- PEOU, Perceived Enjoyment- ENJ, and Perceived Resources- RES) and Intention to Use 5G (INT5G). The path equations of the two hypotheses are:

$$INT5G = \beta_1 \times PERI + \beta_2 \times PU + \beta_3 \times PEOU + \beta_4 \times ENJ + \beta_5 \times RES + \epsilon$$

Where β represents path coefficients of ϵ represents and e is the error term.

4.4 ANN Modelling

An artificial neural network (ANN) model was applied to achieve better complexity and increase accuracy, employing construction predictions in conjunction with SEM results. ANNs require specifications of an architecture. The manufactured model was a multilayer perceptron (MLP) with two hidden layers and a sigmoid activation function. The data was divided into random training (70%) and testing (30%) sets, and cross-validation with 10 folds was implemented to avoid overfitting. Model performance was evaluated in terms of generalized root mean square error (NRMSE) and R-squared. Sensitivity analysis estimated the relative importance of each prophet to employ 5G vs other technologies.

ANN Model

The ANN records nonlinear relationships. Using the following expression, the output $\widehat{INT5}G$ is calculated:

$$\widehat{INT5}G = f(W_2 \cdot h_2 + b_2)$$

Where h_2 is the result of the hidden layer, and f is an activation function. The model will be trained on the minimum Mean Squared Error (MSE).

4.5 Importance–Performance Map Analysis (IPMA)

The IPMA was employed to integrate the importance (overall impact) and performance (mean value) of each construction on the result variable (INT5G). The priority of high-influence constructions, despite comparatively low performance, was identified to inform interventions targeted at increasing reliable 5G penetration.

IPMA assists in the identification of the priority of constructs according to their priority and outputs. It is a combination of the output of SEM (path coefficients) and the performance scores (average scores of the constructs). The following is a summary of the model:

$$\text{Priority of Construct} = f(\text{Importance,Performance})$$

Where Importance is known through path coefficients (b) through SEM, and Performance is known through the mean of the constructs. High importance and low performance constructs are given priority to improve.

5 Findings and Discussion

a. Data Analysis

The model was validated using a two-step methodology, for which we specifically designed each step as Distilled-PLS-SEM Neural Network Dual Strategies (D-PLS-SEM-3-ANN). In step one, D-PLS-SEM-3-ANN trains PLS as stage one on the entire dataset by using a common SEM technique for model validation (measurement as well as structural). Several metrics for model validation, including reliability, convergent validity, and discriminant validity, were assessed to ensure models were as robust as possible. For the next phase, D-PLS-SEM-3-ANN models the PLS as a second stage via the entire dataset to train the hidden levels of the neural nets. Each neural net receives as inputs the sem-best-explained-peeled variables and the net outputs the evaluated five models, inner 10-fold cross-validation (IV 10-fold cross-validation). To prevent overfitting while model building, every neural net was optimally designed to ensure the model cross-validated its parameter space, not the data partitions. Each model meta-validated against the other, yielding models A to D and a 5th neural net model with no inputs. All outputs were examined via a neural net mastering the inputs. The PLS-SEM predictive outputs, while building each net model, represented the lack of cross-validated domains in relation to the nonlinearity of the 5G model.

b. Convergent Validity

Table 3 demonstrates the reliability and validity of the various constructs in the study. Cronbach's alpha scores obtained range from 0.769 to 0.918, which are all above the 0.70 threshold and therefore indicate strong internal consistency. The composite reliability (CR) scores ranged from 0.868 to 0.948, thereby confirming construct reliability. The average variance extracted (AVE) scores ranged from 0.688 to 0.859, and all surpassed the 0.50 threshold, which demonstrates convergent validity. These findings, along with other analyses, indicate that the items in the survey were able to capture the latent constructs.

c. Discriminant Validity

The data, which is presented in Table 3, has also been able to measure discriminant validity. The square root of average variance extracted (AVE) for each construct was higher than the respective highest association with other constructs, satisfying the Fornell–Larcker criterion. Furthermore, HTMT ratios lower than 0.85 also provide evidence for discriminant validity. This evidence that the constructs measured are statistically different and represent different facets of the 5G behavioral intention indicator.

Discriminate validity of latent variables as presented in Table 4 is evaluated using the Fornell-Larcker criterion. The diagonal values are indeed larger than the correlations among the constructs. For instance, the value INT5G (0.839) exceeds its highest association with PEOU (0.690), which shows the two constructs can be separated. This suggests that the boundaries of the captured latent factors are not conceptually overlapping. This form of validity guarantees that behavioral inferences can be adequately construed in intelligent, untethered spatial environments.

Table 3: Summary of constructs

Variants	Types	Factors	Internal Reliability	CR	Predictive Accuracy	Average Variance Extracted
INT5G	INT5G1	0.850	0.791	0.877	0.800	0.705
	INT5G2	0.797				
	INT5G3	0.869				
PERI	PERI1	0.848	0.918	0.948	0.921	0.859
	PERI2	0.936				
	PERI3	0.904				
PEOU	PEOU1	0.918	0.893	0.907	0.933	0.824
	PEOU2	0.938				
	PEOU3	0.925				
PU	PU1	0.735	0.769	0.868	0.771	0.688
	PU2	0.889				
	PU3	0.856				
ENJ	ENJ1	0.903	0.780	0.874	0.810	0.701
	ENJ2	0.902				
	ENJ3	0.787				
RES	RES1	0.863	0.877	0.886	0.925	0.804
	RES2	0.916				
	RES3	0.942				

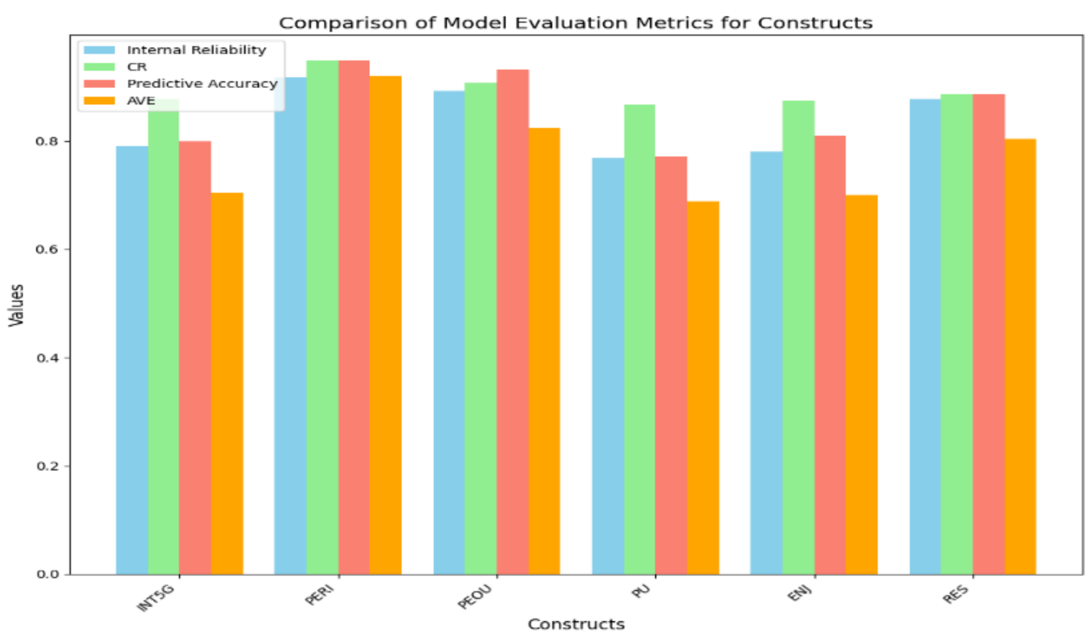

Figure 2: Comparison of model evaluation metrics for constructs

Figure 2 is a comparative analysis of 6 constructs including INT5G, PERI, PEOU, PU, ENJ, and RES on four major evaluation measures namely Internal Reliability, Composite Reliability (CR), Predictive Accuracy, and Average Variance Extracted (AVE). The bars represent each construct, one respectively, and offer a direct comparison of the constructs with one another. The chart assists in evaluating the performance and reliability of every construct in the environment of the 5G adoption model, demonstrating the strengths and areas to improve on the basis of such metrics.

Table 4: Fornell-larcker scale

	INT5G	PERI	PEOU	PU	ENJ	RES
INT5G	**0.839**					
PERI	0.582	**0.927**				
PEOU	0.690	0.637	**0.837**			
PU	0.500	0.625	0.684	**0.908**		
ENJ	0.625	0.695	0.553	0.577	**0.897**	
RES	0.672	0.654	0.558	0.592	0.754	**0.829**

Table 5 illustrates the HTMT values, which offer an improved technique for evaluating discriminant validity. All the inter-construct HTMT ratios are well below the conservative threshold of 0.85, which suggests that constructs such as ENJ, RES, and PERI are empirically distinct. For instance, the HTMT value between PU and RES is 0.714, meaning that they are readily separable. This further test enhances the structure of the measurement model. HTMT analysis further increases the probability that these constructs help explain the adoption behavioral model of users in dependable 5G systems.

Table 5: HTMT analysis

	INT5G	PERI	PEOU	PU	ENJ	RES
INT5G						
PERI	0.679					
PEOU	0.572	0.681				
PU	0.587	0.602	0.556			
ENJ	0.583	0.570	0.512	0.648		
RES	0.457	0.582	0.392	0.714	0.616	

d. Hypothesis Analysis

To analyse the interrelationships of different components of the structural models 'computational constructs, smart PLS structural equation modelling and maximum-likelihood estimation were used to test the structural models. The hypotheses were tested for the models that were proposed. Note the model's predictive improvement as indicated in Table 6 and Figure 3, as it suggests that the models can now explain about 476% of the variance in the intention to use 5G.

Table 6: R^2 outcomes

Constructs	R^2	Outcomes
INT5G	0.476	Moderate

Based on the analysis, Table 7 shows the values of β, t, and p for each of the hypotheses formulated using the PLS-SEM technique. The empirical analysis confirmed hypotheses 1 through 5. 'Intention to use stickers (IUS)' depended on 'Skill readiness within the context of the topic (PERI)' (β= 0.331, P<0.001), 'Perceived usefulness of stickers (PU)' (β= 0.857, P<0.001), 'Perceived ease of use of stickers (PEOU)' (β= 0.277, P<0.001), 'Perceived enjoyment of stickers (ENJ)' (β= 0.465, P<0.001), and 'Perceived resources (RES)' (β= 0.460, P<0.001)' which confirmed hypotheses 1 through 5.

Table 7: Hypothesis testing results using PLS-SEM

Hypothesis	Relationship	Path Coefficient (β)	t-value	p-value	Supported	Implications for Dependable Systems
H1	PERI → INT5G	0.331	3.360	0.001	Yes	Technical readiness boosts user confidence in mobile apps.
H2	PU → INT5G	0.857	5.676	0.006	Yes	Perceived benefits strengthen user trust in 5G services.
H3	PEOU → INT5G	0.277	6.332	0.000	Yes	Simplicity promotes adoption across diverse user bases.
H4	ENJ → INT5G	0.465	6.017	0.000	Yes	Affective satisfaction ensures continued use.
H5	RES → INT5G	0.460	5.537	0.000	Yes	Infrastructure support is crucial for robust deployment.

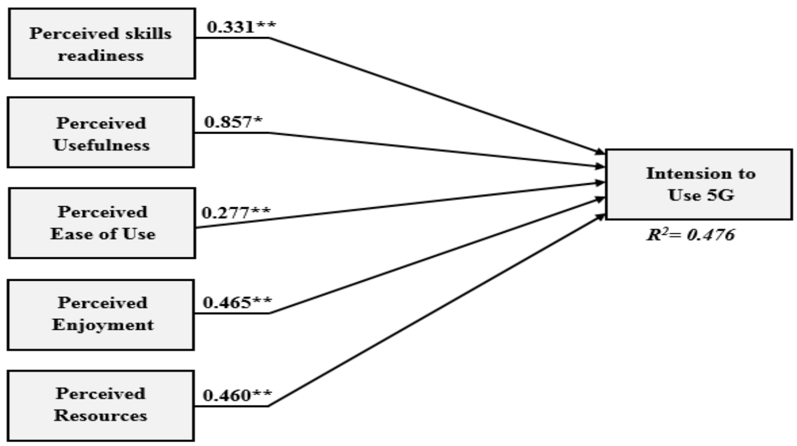

Figure 3: The structural model

Table 7, PLS-SEM's PLS-SEM hypothesis indicates the results of the test. All relationships proposed by the model prove to be important. Regarding the usefulness of a system, the importance of 5G expresses the value of segment acceptance systems the most, with the most potent predictor being β = 0.857. Therefore, this system reflects its importance in acceptance. Happiness and resources also played a significant role, establishing an emotional and infrastructural foundation for the mobile network ecosystem. These findings align with building 5G services that are aware of the situation and reliable. Experimentally confirmed approaches have consistently demonstrated a strong foundation for reporting strategic investments in computing resources worldwide.

e. ANN Model Analysis

The essential predictors derive from the output of PLS-SEM, which serves as the foundation for ANN analysis. ANN analysis is limited to the PERI, PU, PEOU, ENJ, and RES variables. As indicated in Figure 4, PERI, PU, PEOU, ENJ, and RES factor into the ANN model. The architecture "Two-hidden-layer Deep ANN" has made it feasible to perform Deep Learning. The Sigmoid Activation Function has been utilized for the function of the hidden layer and output layer. Hence, in the model of the research, the ranges of the neurons are [0, 1]. To prevent the ANN from overfitting, a 70-30 stratified split was performed using cross-validation, with 70% for training and 30% for validation. The minuscule variations in the RMSE and the standard deviation of training and testing data justify the employment of the ANN for significant precision.

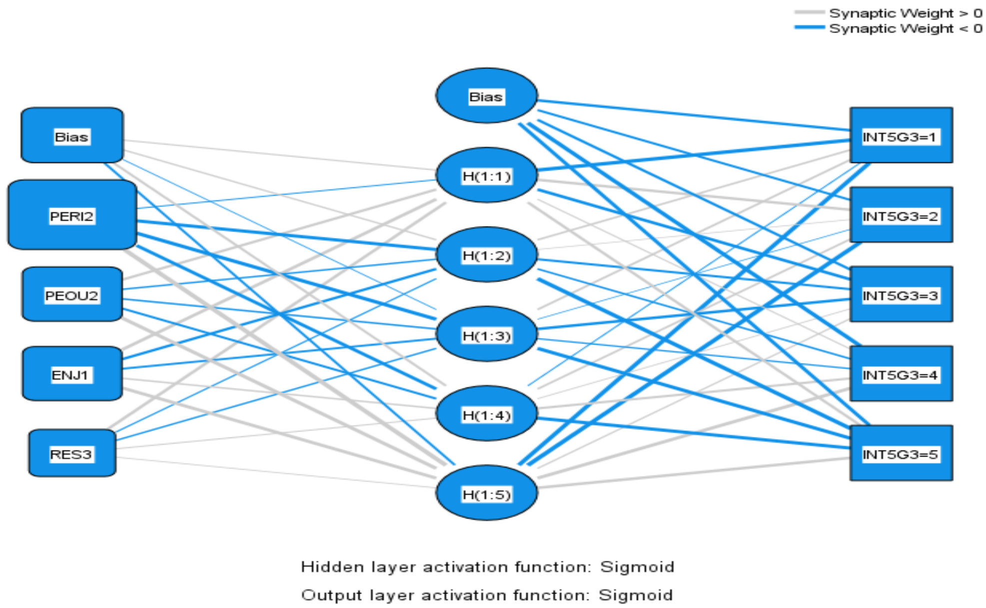

Figure 4: ANN model

Table 8: ANN sensitivity ranking of 5G adoption factors

Predictor	**Raw Importance**	**Normalized importance (%)**	**Priority for Intelligent Mobile Systems**
ENJ	0.465	100.0%	Critical for user engagement in context-aware services
PERI	0.460	98.9%	Vital for supporting skill-aligned deployment
PU	0.218	46.9%	Enhances the functional credibility of 5G systems
PEOU	0.214	46.0%	Low entry barriers expand network coverage and scalability.
RES	0.103	22.2%	Infrastructure optimization is key to operational dependability.

From the analysis of the ANN model in Table 8, among all variables in 5 grams of adoption, the strongest pleasure (ENJ) is considered. This highlights the need for customer-focused, innovative services that enhance the quality of human life. Close Skill Ready (Perry) sets users' purposeful skills as measurement benchmarks for effective system integration. PU and POU have moderate effects on ease of use and management of mobile ecosystems. Infrastructure (RES) is the lowest weighted component of the Ann model, but is essential for the most fundamental level services. These results confirm that a positive strategy is required for the order of components for the manufacture of scalable and reliable 5G applications.

f. Sensitivity Analysis

For the sensitivity analysis computation, the mean value of each factor is applied over the highest value and then expressed as a percentage. For all ANN modeling predictors, the normalized and mean resultant importance are shown in Table 9.

Table 9: Independent variable analysis

	Imp.	Normalized Imp.
PERI	.465	100.0%
PU	.218	46.9%
PEOU	.214	46.0%
ENJ	.272	100.0%
RES	.103	22.2%

Sensitivity analysis in Table 9 outcomes suggests that for behavioral intention, PERI and ENJ are highly significant predictors, followed by PU and PEOU. The application of ANN is also corroborated, and performance and precision are confirmed to be almost identical, as evidenced by the R2 outcome. The ANN possesses an R^2 value that is comparatively greater (80%) than PLS-SEM (R^2 = 47.6%). The ANN technique, when put next to PLS-SEM, elucidates more about the endogenous variables.

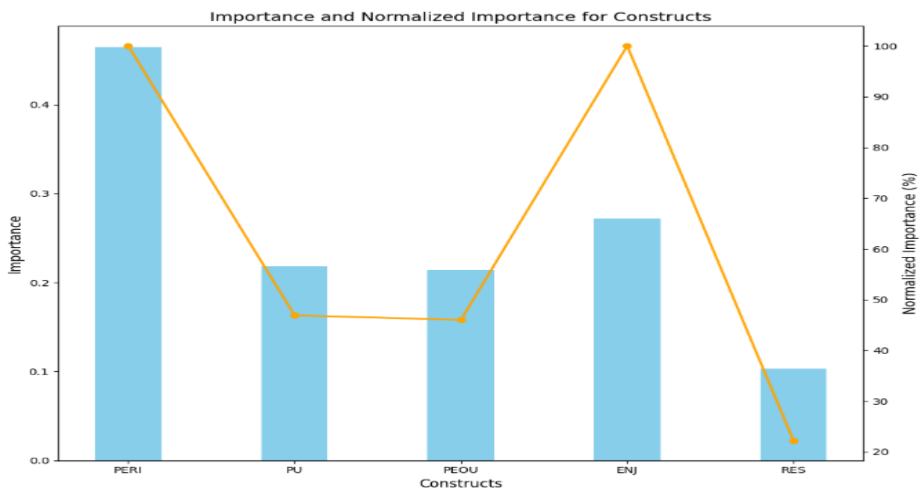

Figure 5: Sensitivity analysis of 5G adoption drivers through ANN

Figure 5 graphically displays the sensitivity rankings of the major determinants of 5G technology adoption, as obtained through the Artificial Neural Network (ANN) analysis. The five key factors that are compared in the graph are: Perceived Skill Readiness (PERI), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Enjoyment (ENJ), and the Perceived Resources (RES). The Importance values show which factors influence the 5G adoption process most of all, and PERI and ENJ have the largest effect, followed by PU and PEOU. The impact of RES on adoption is the lowest. The chart not only shows the relative importance of these factors but also assists in defining where the focus of efforts needs to be put to enhance the chances of the successful adoption of 5G.

g. Importance-Performance Map Analysis

The outcomes of PLS-SEM analysis have to be understood with the help of the Individual Product-Market Assessment IPMA (Ringle and Sarstedt). IPMA can serve as an extension of path coefficient weighing (which is crucial). Nevertheless, IPMA represents the latent variables and average value of their indicators as well (which is a measure of a particular construct). In IPMA, all constituent value metrics indicate all latent value metrics, which serve as a construct of lesser importance when compared to the target value (in this case, behavioral intention).

On the flipside, the average latent construct value signifies the measure of performance. Result of Individual Product-Market Assessments IPMA is provided in Figure 3. We have calculated the performance and importance of five factors: PERI, PU, PEOU, ENJ, and RES. Findings show that RES and ENJ have the highest performance and importance, respectively. Also, the second-highest values are for PEOU, specifically concerning IPMA. Additionally, for PU, the importance measure indicates that the performance measure has the lowest value. The lowest value for the importance measure is for PERI (Figure 6).

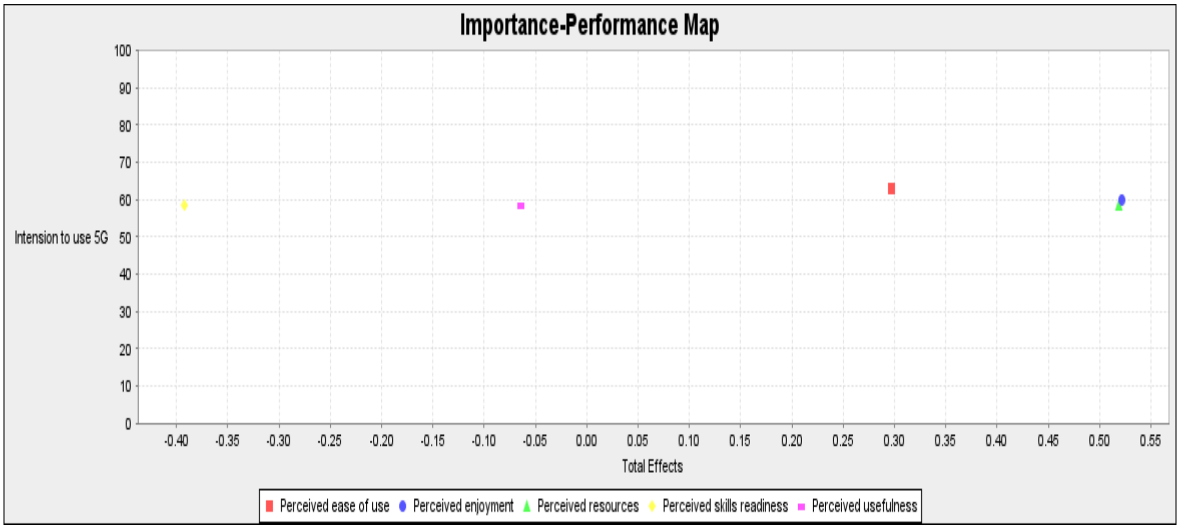

Figure 6: IPMA results

Table 10: Importance performance map analysis

Constructs	Total Effect (Imp.)	Resultant Score	Strategic Priority for Deployment
ENJ	0.465	High	Prioritize user-centered design in intelligent interfaces
RES	0.460	High	Ensure the technical infrastructure supports reliability
PEOU	0.277	Moderate	Maintain usability standards for mobile ecosystems
PU	0.218	Low	Market usefulness through service education
PERI	0.103	Moderate	Invest in digital literacy to boost readiness

The IPMA results in Table 10 satisfactorily inform on user facilitation achievement and closure of the operative area, also integrating 5G into intelligent mobile networks. Perceived enjoyment (ENJ) and resource availability (RES) are both key and crucial, which was outstanding, and a critical success factor for user-driven and reliable service design. Ease of use and skill readiness (peri), which do not eliminate examples of constructions, require continuous and permanent attention to purpose and training. The perceived utility (PU), which was not good, is a concept that facilitates strategic communication and advocacy for the mainly deprived. Such results help ensure a user experience that is enhanced by a robust functional 5G system.

6 Conclusion

This research examined the adoption of 5G technology within the Gulf region and how it can be modeled using a hybrid machine learning and structural equation modeling approach, incorporating TAM's constitutive behavior, experience, and infrastructural components. The results of the studies showed that the most significant positive effect on adoption was due to enjoyment (Enj) and resources (RES). This means that user experience and infrastructure are crucial for the rapid adoption of 5G technology. Estimated skills and ease of use also matter, suggesting adoption will be more with more training and much with very few obstacles. From the perspective of a citation, the integration of the PLS-SEM with the AN demonstrated the accuracy in the future modeling by capturing behavioral non-dialects, which significantly defeats the reforms obtained from the single-phase model. These results highlighted the need for a comprehensive stance strategy among network providers, developers, policymakers, and 5G app ecosystem builders, focusing on their efforts in 5G networks to enhance credibility and purpose. Unlike the current work, future research must extend beyond the Gulf Region, incorporate real-time network performance pavement data, and increase the usage of explainable artificial intelligence to make artificial neural networks more transparent. Furthermore, the adoption of longitudinal studies will be beneficial in scrutinizing 5G-related advancements and their adoption drivers, especially with the increased use of IoT, edge computing, and the gradual integration of early-stage 6 G technologies.

References

[1] Ahad, A., Tahir, M., Aman Sheikh, M., Ahmed, K. I., Mughees, A., & Numani, A. (2020). Technologies trend towards 5G network for smart health-care using IoT: A review. *Sensors*, *20*(14), 4047. https://doi.org/10.3390/s20144047

[2] Ahmad, A. R., Jameel, A. S., & Raewf, M. (2021). Impact of social networking and technology on knowledge sharing among undergraduate students. *International Business Education Journal*, *14*(1), 1-16.

[3] Al-Emran, M., Abbasi, G. A., & Mezhuyev, V. (2021). Evaluating the impact of knowledge management factors on M-learning adoption: A deep learning-based hybrid SEM-ANN approach. In *Recent advances in technology acceptance models and theories* (pp. 159-172). Cham: Springer International Publishing. 335, 159-172. https://doi.org/10.1007/978-3-030-64987-6_10

[4] Al-Maroof, R. S., Akour, I., Aljanada, R., Alfaisal, A. M., Alfaisal, R. M., Aburayya, A., & Salloum, S. A. (2021). Acceptance determinants of 5G services. *International Journal of Data & Network Science*, *5*(4). https://doi.org/10.5267/j.ijdns.2021.8.006

[5] Alrusaini, O. A. (2025). A Hybrid Structural Equation Modeling–Artificial Intelligence Model for Enhancing Cybersecurity of Personal Information in Mobile Applications. *International Journal of Human–Computer Interaction*, 1-16. https://doi.org/10.1080/10447318.2025.2508314

[6] Antoniewicz, B., & Dreyfus, S. (2024). Techniques on controlling bandwidth and energy consumption for 5G and 6G wireless communication systems. *International Journal of communication and computer Technologies*, *12*(2), 11-20. https://doi.org/10.31838/IJCCTS.12.02.02

[7] Antonov, O., Gordiichuk, S., Vitvytska, S., Dubaseniuk, O., Sydorchuk, N., & Kovalchuk, V. (2025). The Impact of Internet Services on Education: Preparing Future Professionals through Innovative Learning Technologies. *Indian Journal of Information Sources and Services*, *15*(3), 183–191. https://doi.org/10.51983/ijiss-2025.IJISS.15.3.21

[8] Asadi, S., Abdullah, R., Safaei, M., & Nazir, S. (2019). An integrated SEM-neural network approach for predicting determinants of adoption of wearable healthcare devices. *Mobile Information Systems*, *2019*(1), 8026042. https://doi.org/10.1155/2019/8026042

[9] Baratè, A., Haus, G., Ludovico, L. A., Pagani, E., & Scarabottolo, N. (2019). 5G technology and its application to e-learning. In *EDULEARN19 Proceedings* (pp. 3457-3466). IATED. https://doi.org/10.21125/edulearn.2019.0918

[10] Dadhich, M., Rathore, S., Gyamfi, B. A., Ajibade, S. S. M., & Agozie, D. Q. (2023). Quantifying the Dynamic Factors Influencing New-Age Users' Adoption of 5G Using TAM and UTAUT Models in Emerging Country: A Multistage PLS-SEM Approach. *Education Research International*, *2023*(1), 5452563. https://doi.org/10.1155/2023/5452563

[11] Gao, Y. (2021). A Survey Study on the Application of Modern Educational Technology in English Major College Teaching in the Age of 5G Communication. *Theory & Practice in Language Studies (TPLS)*, *11*(2). 202–209. https://doi.org/10.17507/tpls.1102.13

[12] Han, G., Zhang, H., Zhang, Z., Ma, Y., & Yang, T. (2024). AI-Based Malicious Encrypted Traffic Detection in 5G Data Collection and Secure Sharing. *Electronics*, *14*(1), 51. https://doi.org/10.1109/ACCESS.2019.2960083

[13] Han, M., & Zhang, X. (2020, November). Prospects for the advancement of the TikTok in the age of 5G communication. In *2020 13th CMI conference on Cybersecurity and privacy (CMI)-digital transformation-potentials and challenges (51275)* (pp. 1-5). IEEE. https://doi.org/10.1109/CMI51275.2020.9322720

[14] Hassan, R. O. S. I. L. A. H., Irsan, M. U. H. A. M. A. D., Nachouki, M. I. R. N. A., Halimatul, N., Ismail, A., & Awwad, S. A. B. (2024). 5G applications via virtual reality technology in education. *Journal of Theoretical and Applied Information Technology*, *102*(13), 5093-5105.

[15] Himawan, H., Hassan, A., & Bahaman, N. (2025). Determination of Factors for the Adoption of Intelligent Transportation Systems (ITS) in Yogyakarta: A Study of Infrastructure, Technology, and Policy. *International Journal of Computer Information Systems and Industrial Management Applications*, *17,* 452-465. https://doi.org/10.70917/ijcisim-2025-0029

[16] Hoo, W. C., Ping, L. S., Hossain, S. F. A., Jia, Y., & Razak, D. A. (2024). Factors Influencing Consumer Purchase Intention and Adoption Onwards of 5G Mobile Phone in Malaysia. *Journal of Ecohumanism*, *3*(3), 1717-1733. https://doi.org/10.62754/joe.v3i3.3526

[17] Ilieva, G., Yankova, T., Ruseva, M., Dzhabarova, Y., Zhekova, V., Klisarova-Belcheva, S., ... & Dimitrov, A. (2024). Factors influencing user perception and adoption of e-government services. *Administrative Sciences*, *14*(3), 54. https://doi.org/10.3390/admsci14030054

[18] Jang, Y., & Kim, S. (2024). Understanding mobile OTT service users' resistance to participation in wireless D2D caching networks. *Behavioral Sciences*, *14*(3), 158. https://doi.org/10.3390/bs14030158

[19] John, J., Noor-A-Rahim, M., Vijayan, A., Poor, H. V., & Pesch, D. (2024). Industry 4.0 and beyond: The role of 5G, WiFi 7, and time-sensitive networking (TSN) in enabling smart manufacturing. *Future Internet*, *16*(9), 345. https://doi.org/10.3390/fi16090345

[20] Kala, D., & Chaubey, D. S. (2024). Perceived value and adoption intention for 5G services in India: Moderating effect of environmental awareness. *Journal of Telecommunications and the Digital Economy*, *12*(2), 16-39.

[21] Kiat, L. S., Hoo, W. C., Cheng, A. Y., Prompanyo, M., & Hossain, S. F. A. (2025). Factors Influencing Intention to use 5G Mobile Technology and Adoption Onwards in Malaysia. *WSEAS Transactions on Business and Economics*, *22*, 773-787. https://doi.org/10.37394/23207.2025.22.68

[22] Kim, H., Kim, S. W., Park, E., Kim, J. H., & Chang, H. (2020). The role of fifth-generation mobile technology in prehospital emergency care: An opportunity to support paramedics. *Health Policy and Technology*, *9*(1), 109-114. https://doi.org/10.1016/j.hlpt.2020.01.002

[23] Lee, V. H., Hew, J. J., Leong, L. Y., Tan, G. W. H., & Ooi, K. B. (2020). Wearable payment: A deep learning-based dual-stage SEM-ANN analysis. *Expert systems with Applications*, *157,* 113477. https://doi.org/10.1016/j.eswa.2020.113477

[24] Leong, L. Y., Hew, T. S., Ooi, K. B., Lee, V. H., & Hew, J. J. (2019). A hybrid SEM-neural network analysis of social media addiction. *Expert systems with Applications*, *133*, 296-316. https://doi.org/10.1016/j.eswa.2019.05.024

[25] Maeng, K., Kim, J., & Shin, J. (2020). Demand forecasting for the 5G service market considering consumer preference and purchase delay behavior. *Telematics and Informatics*, *47*, 101327. https://doi.org/10.1016/j.tele.2019.101327

[26] Mahadevan, P., Alabdeli, H. M., Sapaev, I. B., Berejnov, I., Madrakhimova, D., & Udayakumar, R. (2025). Dual connectivity management in 5G mobile internet infrastructures. *Journal of Internet Services and Information Security*, *15*(2), 256–270. https://doi.org/10.58346/JISIS.2025.I2.018

[27] Mustafa, S., Zhang, W., Anwar, S., Jamil, K., & Rana, S. (2022). An integrated model of UTAUT2 to understand consumers' 5G technology acceptance using SEM-ANN approach. *Scientific Reports*, *12*(1), 20056. https://doi.org/10.1038/s41598-022-24532-8

[28] Naji, K. K., Gunduz, M., & Al-Qahtani, A. (2024). Unveiling Digital Transformation: Analyzing Building Facility Management's Preparedness for Transformation Using Structural Equation Modeling. *Buildings*, *14*(9), 2794. https://doi.org/10.3390/buildings14092794

[29] Ofoghi, R. (2015). Technical and structural analysis of the wireless networks, safety and security analysis of wireless and cable networks. *International Academic Journal of Science and Engineering*, *2*(1), 39–44.

[30] Osee, K. M. T., Nkemeni, V., & Sone, M. E. (2025). Quality of Experience Management in Mobile Networks: Techniques, Constraints, and Emerging Trends for Value-Added Services. *Computer Networks and Communications*, 21-58. https://doi.org/10.37256/cnc.3220256766

[31] Oyeniran, C. O., Adewusi, A. O., Adeleke, A. G., Akwawa, L. A., & Azubuko, C. F. (2023). 5G technology and its impact on software engineering: New opportunities for mobile applications. *Computer Science & IT Research Journal*, *4*(3), 562-576. https://doi.org/10.51594/csitrj.v4i3.1557

[32] Peng, R., Lou, Y., Kadoch, M., & Cheriet, M. (2020). A human-guided machine learning approach for 5G smart tourism IoT. *Electronics*, *9*(6), 947. https://doi.org/10.3390/electronics9060947

[33] Pethuraj, M. S., bin Mohd Aboobaider, B., & Salahuddin, L. B. (2023). Analyzing QoS factor in 5 G communication using optimized data communication techniques for E-commerce applications. *Optik*, *272*, 170333. https://doi.org/10.1016/j.ijleo.2022.170333

[34] Q. Hugh, & Freddy Soria. (2025). Resource-Aware Network Slicing for QoS-Driven Service Orchestration in Integrated Satellite–5G Systems. *ECCSUBMIT Conferences*, *3*(2), 70–75. https://doi.org/10.17051/ECC/03.02.09

[35] Quasim, M. T., Nisa, K. U., Husain, M. S., Aadam, A. I. A., Sheraz, M. W., & Khan, M. Z. (2025). Intelligent Management of Resources for Smart Edge Computing in 5G Heterogeneous Networks Using Blockchain and Deep Learning. *Computers, Materials & Continua*, *84*(1). 1169. https://doi.org/10.32604/cmc.2025.062989

[36] Saflor, C. S., Mariñas, K. A., Alvarado, P., Baleña, A., Tanglao, M. S., Prasetyo, Y. T., ... & Bernardo, E. (2024). Towards Sustainable Internet Service Provision: Analyzing Consumer Preferences through a Hybrid TOPSIS–SEM–Neural Network Framework. *Sustainability*, *16*(11), 4767. https://doi.org/10.3390/su16114767

[37] Sellami, B., Hakiri, A., & Yahia, S. B. (2022). Deep Reinforcement Learning for energy-aware task offloading in join SDN-Blockchain 5G massive IoT edge network. *Future Generation Computer Systems*, *137*, 363-379. https://doi.org/10.1016/j.future.2022.07.024

[38] Senthil, G. A., Prabha, R., Roopa, D., & Sridevi, S. (2025). An Enhanced Sustainable Mobility as a Service Based on 5G Network for Human-Centric Mobile Network in Smart City. *Digital Convergence in Intelligent Mobility Systems*, 293-314. https://doi.org/10.1002/9781394275274.ch13

[39] Shao, J., Bai, H., Shu, S., & Joppe, M. (2020). Planners' perception of using virtual reality technology in tourism planning. *E-review of Tourism Research*, *17*(5). 685-695

[40] Sharma, S. K., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. *International Journal of Information Management*, *44*, 65-75. https://doi.org/10.1016/j.ijinfomgt.2018.09.013

[41] Sohaib, O., Hussain, W., Asif, M., Ahmad, M., & Mazzara, M. (2019). A PLS-SEM neural network approach for understanding cryptocurrency adoption. *IEEE Access*, *8*, 13138-13150.

[42] Song, P., Lee, J., Abdelmoniem, A. M., & Mukhanov, L. (2025). Unlocking the power of 4G/5G mobile networks: An empirical dive into quality and energy efficiency in YouTube Edge services. *Computer Networks*, 267, 111344. https://doi.org/10.1016/j.comnet.2025.111344

[43] Thooyamani, K. P., Khanaa, V., & Udayakumar, R. (2014). Wide area wireless networks-IETF. *Middle-East Journal of Scientific Research*, *20*(12), 2042-2046.

[44] Trevlakis, S. E., Pappas, N., & Boulogeorgos, A. A. A. (2024). Toward natively intelligent semantic communications and networking. *IEEE Open Journal of the Communications Society*, *5*, 1486-1503. https://doi.org/10.1109/OJCOMS.2024.3371871

[45] Waqar, A., Shafiq, N., Othman, I., Alsulamy, S. H., Alshehri, A. M., & Falqi, I. I. (2024). Deterrents to the IoT for smart buildings and infrastructure development: A partial least square modeling approach. *Heliyon*, *10*(10). 1-20. https://doi.org/10.1016/j.heliyon.2024.e31035

[46] Wu, J., & Yu, Z. (2025). Research on Adoption Intention Toward Intelligent Messaging Service: From Self-Determination Theory Perspective. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(2), 83. https://doi.org/10.3390/jtaer20020083

[47] Xu, X., Li, D., Sun, M., Yang, S., Yu, S., Manogaran, G., ... & Mavromoustakis, C. X. (2019). Research on key technologies of smart campus teaching platform based on 5G network. *IEEE Access*, *7*, 20664-20675. https://doi.org/10.1109/ACCESS.2019.2894129

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Dr. Mohammed Mhmood Al Matalka has an extensive academic experience in various educational institutions within UAE and abroad teaching Arabic language as well as Arabic as a second language. The Academic journey of Dr. Al-Matalka extends to developing and reviewing the curriculums in number of the Academic institutions including Rabdan Academy. Some of these curriculums are: Arabic Language, Communication Skills, Emirates Studies, Arabic as a Second Language and Learning Skills for new students. Dr. Al-Matalka has participated in the Academia by presenting and publishing his research in various countries as UAE, Malaysia, Jordan and Tunisia. His research focuses on the Quality of Higher Education and Arabic Language. Also, He was a moderator and reviewer in various conference panels. Alongside with his teaching and research, Dr. Al-Matalka is an active member in Academic committees such as: Interviewing Candidate Faculty Members, Academic Support, Developing the Academic Performance, Interviewing Prospective Students. Moreover, He presents number of workshops related to the strategy of education and the education technology.