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Hybrid Partial Least Squares-Structural Equation Modelling and Multi-Layer Perceptron for Predicting E-Participation Success in E-Government Services: Socio-Cultural Insights and Extended Validation

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ABSTRACT

Although the Delone and McLean IS Success Model (D&M) can explain the phenomenon of e-participation success (EPS), the model was initially created in an e-commerce setting and thus neglects external factors related to e-government services. To address the gap, this study revisits the D&M by extending it with four socio-cultural constructs of Trust (TR), Anonymity (AN), Nationalism (NT), and Culture (CR). Based on 428 survey data from Malaysian citizens, a hybrid methodology was employed, integrating Partial Least Squares-Structural Equation Modelling (PLS-SEM) and Multi-layer Perceptron (MLP) to capture non-linear relationships and enhance predictive accuracy. While hybrid modelling is common, past studies have often applied limited classification metrics, and the infrequent use of comprehensive metrics, such as Area Under the Receiver Operating Characteristic Curve (AUC-ROC), may potentially affect the reliability and generalizability of these models. A comparative R^2 analysis between the baseline and enhanced models in this study revealed significant improvements, with R^2 for e-participation intention (EPI) increased from 0.620 to 0.728, EPS from 0.330 to 0.345, while User Satisfaction (US) remained strong at 0.765. The analysis predicts a 94.80% success rate for e-participation, with the MLP model further demonstrating robust classification performance, achieving an accuracy of 90.1%, a precision of 0.909, a recall of 0.948, an F1 score of 0.928, and an AUC-ROC of 0.955, outperforming other benchmark classifiers. This study contributes theoretically by introducing underexplored socio-cultural variables into the D&M while methodologically extending the hybrid PLS-SEM and MLP through a robust model validation using AUC-ROC.

Keywords: Artificial neural network, Delone and McLean IS Success Model, e-government, e-participation, hybrid analysis.

INTRODUCTION

Governments worldwide have increasingly invested in Information and Communication Technology (ICT) to improve the efficiency, transparency, and accessibility of public sector services (Du, 2017; United Nations, 2022b). The digital transformation of government services has introduced innovative mechanisms that facilitate participatory decision-making, a core objective of e-government initiatives (Sofyani et al., 2020). This transformation shifts governance paradigms by emphasising collaborative engagement between citizens and governments, fostering democratic principles such as openness, transparency, accountability, and responsiveness (Sofyani et al., 2020). Unlike the traditional perception of citizens as passive recipients of public services, the e-government framework positions them as active collaborators in promoting and upholding democratic norms (Kamarudin et al., 2019; Sofyani et al., 2020).

Technological tools, such as online budget consultations, electronic feedback systems, and virtual town halls, can enhance citizen-government interaction by providing greater government transparency, responsiveness, and accountability (Prakrit et al., 2019). However, the success of these initiatives still relies on citizens' perceptions of trustworthiness that will further influence their behavioural intentions toward e-participation. Therefore, most Information Systems (IS) researchers perceived trust as an essential factor in the adoption of e-government initiatives (Abdulkareem et al., 2022; Krishnan et al., 2017; Prakrit et al., 2019). Moreover, e-participation intention (EPI) is also posited to play a significant role in driving citizen engagement in decision-making, thereby contributing to the overall success of e-government and e-participation initiatives (Baldi et al., 2023; Dahalin et al., 2019; Mishra & Shah, 2023).

Although a vast literature addresses the impact of e-government on citizen participation (Basri et al., 2019), empirical evidence remains inadequate, particularly in the context of developing countries, such as Malaysia. The Malaysian government has devoted significant resources to ICT to modernise public services and foster citizen engagement across its ministries, departments, and agencies (Baldi et al., 2023). Unfortunately, it appears that these investments have yet to reach equilibrium. For instance, the United Nations E-Government Development Index (UNEGDI) ranked Malaysia 47th and 29th in the e-government and e-participation indices, respectively, in 2020, and 53rd and 47th in 2022 (United Nations, 2022a). These rankings suggest low citizen engagement in e-government activities, particularly in policy development processes, which raises concerns about the effectiveness of e-government systems in promoting citizen involvement.

Based on the preceding arguments, this study aims to examine the determinants and predict e-participation success (EPS) in e-government services. E-participant adoption and implementation can be viewed through the lens of many existing IS theories and models, including the Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), Unified Theory of Technology Acceptance and Use of Technology (UTAUT) and the updated DeLone and McLean IS Success Model (D&M). While most of these models and theories commonly focus on IS usage, the D&M framework (DeLone & McLean, 2003) is considered the most comprehensive, explicitly developed to understand IS success. However, D&M is still subject to several limitations. First, it involves recursive relationships that may exacerbate the model's common method bias (CMB) issues, potentially leading to inflated correlations between constructs and reduced construct validity (Iqbal & Rafiq, 2023). Secondly, the D&M's predictability of EPS in e-government services remains limited, particularly in capturing context-specific issues such as culture, trust, anonymity, and nationalism (Adnan et al., 2022).

In terms of methodology, Partial Least Squares-Structural Equation Modelling (PLS-SEM) is widely used in exploratory-based IS research to test theoretical models and examine causal relationships (Hair, Hult, et al., 2014; Henseler et al., 2016). The flexibility of PLS-SEM in terms of sample size and complexity assumptions makes it a popular choice among researchers. However, although this technique is considered better at handling non-parametric data compared to Covariance-Based SEM, it is still limited in capturing non-linear and complex patterns in data (Chong, 2013; Sarstedt et al., 2014). These limitations may potentially impact predictive accuracy, particularly in the context of e-government, where user perceptions often exhibit non-linear dynamics (Shmueli et al., 2016).

As a solution to this deficiency, PLS-SEM is sometimes combined with Multi-layer Perceptron (MLP), a technique in Artificial Neural Networks (ANN) (Almarzouqi et al., 2022a; Chong, 2013). However, prior studies combining PLS-SEM with MLP have primarily focused on improving predictive accuracy, without sufficiently addressing validation robustness (Albahri et al., 2022; Richter & Tudoran, 2024). This limitation could reduce the reliability and generalizability of these models, especially in complex domains like e-government, where socio-cultural factors are posited to influence user behaviour (Guo, 2023).

To address the preceding theoretical and methodological gaps, this study aims to develop an EPS model for e-government services, which will later be used as input to a hybrid PLS-SEM and MLP EPS prediction model. Unlike prior studies that focused solely on predictive accuracy, this study conducts a more comprehensive validation by including classification metrics such as accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC), as well as benchmarking the performance of the MLP model against alternative classifiers, such as 5-Nearest Neighbours and Naive Bayes. This article is organised into several sections. Following the Introduction, the Related Works section reviews existing studies and identifies areas that this study aims to address. The Theoretical Background outlines the research model and the development of hypotheses. The Methodology section describes the methods employed, while the Analysis and Findings section presents the results of the PLS-SEM and MLP analyses. Finally, the Conclusion section highlights the study's contributions and proposes future work.

RELATED WORKS

As previously mentioned, the application of PLS-SEM in IS research has become common due to its flexibility in testing theoretical models and examining causal relationships (Hair, Sarstedt, et al., 2014; Henseler et al., 2016). Despite its popularity, PLS-SEM nonetheless has limitations in predicting e-participation in e-government services, where user behaviour and perceptions can exhibit significant non-linear dynamics (Chong, 2013; Shmueli et al., 2016). Past researchers have addressed this issue by exploring hybrid approaches that combine PLS-SEM with machine learning techniques. Although many machine learning techniques can be adopted for this purpose, including Random Forests, Gradient Boosting, and Support Vector Machines, ANN techniques are particularly advantageous for hybrid frameworks, as they excel at capturing non-linear data patterns and offer scalability in handling complex datasets (Kurani et al., 2023).

It explains why studies on the hybridisation of PLS-SEM and ANN are readily available, and their number is growing. However, much of this work has focused on general contexts, such as economy/fintech (Sohaib et al., 2020; Wong et al., 2024), or education (Almufarreh, 2024; Dang et al., 2023), with studies specifically addressing e-government and e-participation being scarce. Even among existing studies, there is often a lack of exploration into the unique socio-cultural factors that may influence citizens' acceptance of e-participation systems, as demonstrated by Wang et al. (2024). Different contexts may present unique challenges. In the case of e-participation, trust, anonymity, culture, and nationalism have been identified as influential factors and should not be overlooked when examining EPS (Afshan & Sharif, 2016; Alarabiat et al., 2021; Alomari et al., 2014; Halych & Demydkin, 2021; Pennington et al., 2004; Tlaiss & Kauser, 2011).

MLP is considered the best choice compared to other ANN techniques when working with structured data, moderate sample sizes, and hybrid frameworks (Albahri et al., 2022). This notion is proven by several studies that demonstrated an enhancement in predictive accuracy through the integration of PLS-SEM and MLP. For example, Li et al. (2019) have demonstrated an effective modelling of complex behaviours in technology adoptions. Similarly, Almarzouqi et al. (2022b) have empirically demonstrated the ability of a hybrid PLS-SEM and MLP framework to handle non-linear relationships in the prediction of metaverse system adoption. However, these studies primarily focused on improving predictive accuracy, with less attention given to incorporating comprehensive validation metrics. As in the case of EPS, model performance in predicting the likelihood of implementation success or failure based on the data is a crucial aspect that should not be overlooked (Naidu et al., 2023). It can be done using the AUC-ROC. Table 1 summarises the evaluation method of previous studies that combine PLS-SEM and ANN analyses.

Table 1

Summary of Previous Studies Combining PLS-SEM and ANN

Author (s)	Focus	Base Model	Validation Metrics	Remarks
Minh et al. (2023)	Factors influencing the use and satisfaction with online civil contracts using a dual-stage PLS-SEM and DNN.	TAM	PLS-SEM: Path coefficients, R^2 values; DNN: RMSE, MAE	• TAM is applied without introducing new constructs. • Evaluation metrics (R^2, RMSE, MAE) may not comprehensively assess performance for classification tasks.
Shahzad et al. (2020)	Factors influencing user adoption of a mobile government security response system.	UTAUT	Accuracy, Precision, Recall, F1 Score	• Modifies UTAUT by incorporating Perceived Mobile Security and Response Efficiency, but lacks consideration of socio-cultural factors such as trust, anonymity, nationalism, and culture. • Metrics focus solely on classification.
Al-Sharafi et al. (2023)	Factors influencing Cloud Computing Integration in SMEs.	Technology–Organisation–Environment (TOE) Framework	PLS-SEM: Path coefficient, R^2 values; ANN: Normalized Importance	• Expands TOE with Cost Reduction and Government Support, relevant but not new contributions. • Normalised Importance in ANN lacks diagnostic capabilities for classification.
Sohaib et al. (2020)	Factors influencing cryptocurrency adoption.	TRI and TAM	PLS-SEM: Path coefficient, R^2 values; ANN: RMSE, MAE	• Integrates TRI with TAM but does not introduce new theoretical variables. • ANN metrics (RMSE, MAE) lack insights into classification capabilities.
Sangwan et al. (2024)	Factors influencing students' satisfaction with emergency remote teaching	Stimulus–Organism–Response (S–O–R) Theory	PLS-SEM: Path coefficient, R^2 values; ANN: RMSE, MAE	• Adds Self-Regulated Learning and Internet Self-Efficacy as adaptations rather than new constructs. • ANN metrics fail to capture diagnostic insights on satisfaction levels.

(continued)

Author (s)	Focus	Base Model	Validation Metrics	Remarks
Qiu and Zhou (2023)	Factors influencing citizens' willingness and behaviour in digital rural governance.	TPB and Motivation-Opportunity-Ability (MOA) Model	SEM: Path coefficients, R^2 values; ANN: Relative Importance of Predictors	• Combines TPB and MOA, adding Digital Literacy and Opportunity, which are relevant but extensions of existing theories. • Lacks critical insights for classification without advanced metrics.
Alhumaid et al. (2021)	Factors influencing mobile learning usage during the COVID-19 pandemic.	D&M	SEM: Path coefficients, R^2 values; ANN: RMSE, MAE	• Enhances D&M with Institutional Policy and Top Management Support, but does not address the unique dynamics of e-participation. • Metrics (RMSE, MAE) are insufficient for classification tasks.
Wang et al. (2024)	Determinants of citizen engagement intentions via mobile government social media during emergencies.	Self-Regulation Framework, Media Richness Theory, Good Governance Theory, Media Dependency Theory	SEM: Path coefficients, R^2 values; ANN: RMSE, MAE	• Introduces Citizen Trust, Social Media Dependency, and Citizen Satisfaction as extensions of existing theories. • Metrics such as RMSE and MAE do not differentiate between engagement intention levels.

As shown in Table 1, most existing studies are located in the domains of economics/finance (Al-Sharafi et al., 2023; Sohaib et al., 2020) and education (Alhumaid et al., 2021). These studies primarily aim to understand factors influencing the adoption, satisfaction, or integration of systems in their respective contexts. Conversely, in the e-government and e-participation domain, hybrid models are scarce. In terms of the base model, although D&M and other IS adoption models have been applied in existing hybrid studies, they often neglect socio-cultural factors that significantly influence e-participation. For example, while some studies adapt models to include constructs such as Perceived Security or Digital Literacy (Alhumaid et al., 2021; Qiu & Zhou, 2023; Shahzad et al., 2020), they often lack deeper explorations of socio-cultural dimensions, including trust, anonymity, nationalism, and culture. These factors are particularly critical in e-government settings, where both technical system attributes and societal dynamics shape user engagement.

Furthermore, another notable limitation across these studies lies in the type of ANN utilised in conjunction with PLS-SEM. Some studies rely on simpler architectures such as Feedforward Neural Networks (FNN) (Wang et al., 2024), while others use Deep Neural Networks (DNN) (Minh et al., 2023). Compared to DNNs, DNNs are often computationally intensive and prone to overfitting, especially in moderate-sized datasets typical of social science research (Liu et al., 2023). Very few studies use MLPs, which are relatively suitable for hybrid models due to their ability to capture complex, non-linear relationships while maintaining computational efficiency and interpretability (Nasarudin et al., 2023). Compared to DNNs, MLPs are less prone to overfitting and more adaptable to smaller datasets, while offering greater flexibility and scalability than FNNs.

In terms of validating hybrid frameworks, while PLS-SEM provides a foundation for theoretical insights, its combination with ANN is often validated using simplistic metrics, such as accuracy or F1-score (Shahzad et al., 2020; Sharma et al., 2024). These metrics, while indicative of general performance, fail to assess the model's discriminatory power across decision thresholds or its robustness to imbalanced data. The lack of advanced validation compromises the predictive reliability of such models in real-world applications, particularly in domains such as e-participation, where accurately predicting user success and engagement is crucial. Overall, the analysis of previous works has revealed several gaps that this study aims to address. First, the study extended the D&M by incorporating several socio-cultural constructs that enhance the predictive accuracy of the model. Second, using the MLP technique, the rigour of validation metrics will be increased by employing AUC-ROC to evaluate the model's effectiveness in distinguishing between varying levels of EPS.

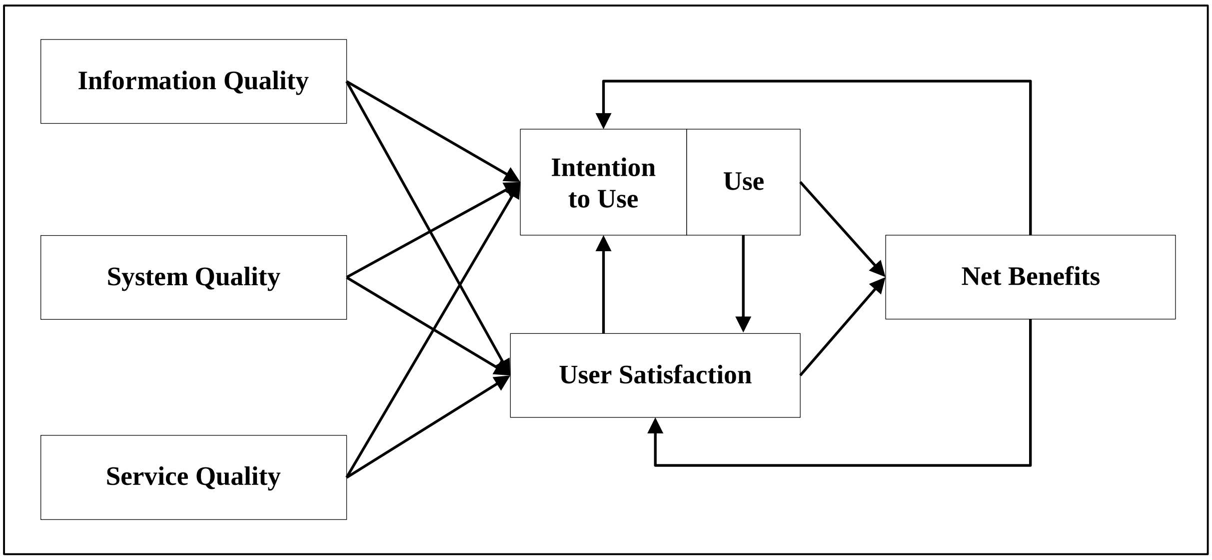
Theoretical Background

The D&M, illustrated in Figure 1, is commonly employed to evaluate the influence of IS qualities on the e-government success (Stefanovic et al., 2021). Initially introduced in 1992, this model identifies key factors influencing IS success, including information quality (IQ), system quality (SYQ), usage, user satisfaction (US), individual impacts, and organisational impacts (DeLone & McLean, 1992). The model was further refined to include service quality (SEQ) as a success measure, emphasising its adaptability to the evolving nature of IS. The revised model delineates interrelationships between quality dimensions (information, system, and service qualities), actual usage or intention to use, US, and net benefits (NB) (DeLone & McLean, 2003).

The D&M asserts that the success of an IS project is influenced by the impact of quality dimensions on actual use, intention to use, and NB. IQ hinges on accuracy, completeness, relevance, and ease of comprehension, while SYQ considers technical design elements such as navigation, ease of use, privacy, and security. SEQ depends on IS's responsiveness and reliability. These critical dimensions were identified by DeLone and McLean (2003) as influencing IS usage, satisfaction and perceived benefits. They are also essential in shaping citizens' perceptions of e-government services, where users heavily rely on virtual services. Hence, the ability of D&M to explain various contexts of e-government success is undeniable, as proved by a large number of past studies (Abdulkareem et al., 2022; Krishnan et al., 2017; Profile, 2022). It makes D&M the most suitable model to examine EPS in e-government services.

Figure 1

The Updated DeLone and McLean IS Success Model



Research Model and Hypotheses

Issues in IS are commonly viewed through the lens of theories and models. However, different contexts may have unique challenges; therefore, existing theories and models are unlikely to directly and fully predict them. For this reason, researchers are highly encouraged to modify the base model to suit the specific needs of the context (DeLone & McLean, 2003). For investigating IS success, the D&M is considered the most comprehensive adoption model in IS and has been applied in diverse IS domains, including e-banking, online shopping, e-health, e-commerce, and e-government. Hence, it is considered the most appropriate approach for examining EPS in e-government services; however, it is subject to certain modifications, as suggested by DeLone and McLean (2003). Several extensions and modifications were made in response to the call preceding the extensive literature review. Some of these include the inclusion of trust (TR), anonymity (AN), culture (CR), and nationalism (NT), which have been identified as influential factors in EPS (Afshan & Sharif, 2016; Alarabiat et al., 2021; Alomari et al., 2014; Halych & Demydkin, 2021; Pennington et al., 2004; Tlaiss & Kauser, 2011). Thus, they have been added to the research model, as shown in Figure 2.

This study also adjusted the model's structure, eliminating the recursive relationships. The process involved determining stronger relationships, with the intention of reducing the possibility of CMB existence, as proposed by Awang et al. (2018). In summary, the research model posits that e-government and e-participation qualities, along with other predictors, will influence the intention to continue participating electronically in government services in the US. It will further increase participation success with trust in (government and technology) serving as mediators. This adaptation aims to capture the political nature of e-government better and addresses issues with the construct of 'use' in the original model. The following sections will discuss the development of the hypotheses of the study.

Impact of IQ on the US

This study proposes that IQ has a significant influence on the US of e-government platforms. Drawing from the D&M (DeLone & McLean, 2003), IQ is conceptualised as the accuracy, timeliness, relevance, and completeness of information provided by an IS. In the context of e-government and e-participation, citizens rely heavily on high-quality information to make informed decisions, navigate services, and contribute effectively. This reliance is heightened due to the intangible nature of online services, where users lack physical interaction and instead depend on the system's informational integrity (Abdulkareem et al., 2022; Krishnan et al., 2017). High-quality information enhances the US by minimising the uncertainty and frustration commonly associated with incomplete or outdated information (Stefanovic et al., 2021). Research in related domains, such as e-commerce and e-learning, also confirms that IQ directly contributes to positive user evaluations (Yao & Xu, 2022). Thus, this study hypothesises:

H1: IQ has a significant positive effect on the US among e-government users.

Impact of IQ on EPI

This study posits that IQ directly influences EPI by shaping citizens' perceptions of the platform's reliability. High-quality information builds trust, enhances usability, and increases citizens' willingness to engage in e-participation (Sofyani et al., 2020). In e-government, where decisions often rely on accurate and timely information, any perceived lack of credibility or completeness can deter user involvement (Shaikh, Almusharraf, et al., 2023; Shaikh, Baig, et al., 2023). Conversely, when citizens perceive information as consistent, accurate, and relevant, they are more likely to view the platform as a reliable channel for civic engagement. It could be argued that without high-quality information, even the most well-designed systems are at risk of failing to gain traction, as citizens cannot make informed decisions. Additionally, in the context of intangible government services, the absence of transparent and accurate information undermines confidence, further discouraging participation. Therefore, robust information quality is essential not just for attracting initial users but for sustaining ongoing engagement. Accordingly, this study hypothesises:

H2: IQ has a significant positive effect on EPI among e-government users.

Impact of SYQ on US

SYQ, which includes technical reliability, responsiveness, and user-friendliness, is proposed to have a great influence on US in the context of e-government. When citizens encounter seamless and error-free systems, their confidence in the platform increases, leading to greater satisfaction (DeLone & McLean, 2003; Stefanovic et al., 2021). Conversely, technical failures, such as poor navigation or long loading times, would negatively affect user experience and satisfaction levels (Petter et al., 2008). In e-government, where users rely heavily on digital systems, SYQ is crucial for fostering positive perceptions (Patergiannaki & Pollalis, 2024). Research has consistently highlighted the role of SQY in shaping US across sectors like e-commerce and online learning (Tam & Oliveira, 2017). Ensuring high SQY not only promotes user engagement but also encourages the adoption of e-government services, which is essential for the successful implementation of digital government initiatives. It can also lead to greater transparency, trust and satisfaction in government processes, and enhance democratic participation among citizens. Thus, this study hypothesises:

H3: SYQ has a significant positive effect on US among e-government users.

Impact of SQY on EPI

This study argues that SYQ influences EPI by enabling efficient and reliable interactions. Technical functionality, including fast response times, ease of use, and system adaptability, encourages users to engage with e-government platforms (Stefanovic et al., 2021). Citizens are more likely to participate in e-governance activities when systems offer a seamless user experience without technical disruptions (Petter et al., 2008). Indeed, this notion has been confirmed by several previous studies (Al-Shammari, 2023; Lee & Tseng, 2018). A reliable SQY enhances user empowerment by enabling smoother navigation and successful task completion. This perceived control over the interaction process reinforces users' confidence in e-government platforms, which is a critical antecedent to behavioural intentions (Venkatesh et al., 2003). For example, platforms that are accessible and responsive are more likely to engage citizens with limited technical expertise, thereby expanding the inclusivity of e-participation. The scalability of high-quality systems to handle increasing user demands without sacrificing performance further enhances their credibility, encouraging sustained participation. On the contrary, technical issues such as frequent crashes, errors, or slow performance can lead to frustration and reduced trust, deterring users from participating in digital governance activities. Therefore, the following hypothesis is made.

H4: SYQ has a significant positive effect on EPI among e-government users.

Impact of SEQ on US

SEQ in the context of e-government refers to the degree of responsiveness, reliability, and empathy demonstrated by the platform in addressing users' needs. High-quality service delivery fosters a sense of trust and fulfilment among users, leading to increased satisfaction levels (Iqbal & Rafiq, 2023; Kettinger & Lee, 1994). Users who receive timely and effective responses to their inquiries are more likely to perceive the platform as efficient and supportive, thereby enhancing their overall experience (Tam & Oliveira, 2017). Conversely, poor SEQ, such as delayed responses or unhelpful interactions, diminishes user confidence and discourages future engagement. In e-government, where services are often intangible and interactions occur through digital channels, the perception of SEQ becomes even more critical. Research has consistently shown that SEQ is one of the strongest predictors of US in various online platforms, including e-commerce and e-learning (Stefanovic et al., 2021). Moreover, e-government services that exhibit high levels of empathy, such as personalised assistance and proactive engagement, are particularly effective in meeting the expectations of diverse user groups. This inclusivity further strengthens US by ensuring that individuals feel valued and supported throughout their interaction with the platform. The preceding argument led to this hypothesis:

H5: SEQ has a significant positive effect on US among e-government users.

Impact of SEQ on EPI

This study hypothesised that SEQ plays a critical role in shaping users' intentions to engage in e-government participation. In the digital environment, where personal interactions are minimal, users rely heavily on the responsiveness, reliability, and overall effectiveness of the platform to form their engagement intentions. High SEQ, characterised by timely responses, personalised interactions, and clear communication, builds trust and motivates citizens to participate in decision-making processes through e-government platforms (Berry et al., 1988; Kettinger & Lee, 1994). Furthermore, SEQ enhances the perceived value of participation by minimising frustrations and creating a seamless user experience (Hsieh et al., 2012). When users feel that their concerns are addressed promptly and accurately, their confidence in the system grows, making them more likely to engage in e-participation activities. Previous research in online service contexts, such as e-commerce and e-learning, has demonstrated that high SEQ positively correlates with user engagement and trust, which are critical antecedents of EPI (Tam & Oliveira, 2017; Venkatesh et al., 2012). This evidenced the importance of SEQ in shaping citizens' attitudes to engage in e-governance activities actively. Therefore, the following hypothesis is proposed.

H6: SEQ has a significant positive effect on EPI among e-government users.

Impact of NB on EPI

NB refers to the overall value perceived by users when engaging with e-government platforms, encompassing both tangible and intangible gains such as time savings, convenience, and perceived effectiveness in influencing governance. When citizens perceive high NB from using an e-government platform, they are more likely to participate in digital governance activities through e-participation platforms. Providing significant personal or collective benefits, such as transparency in decision-making and improved public service delivery, enhances attitude towards future engagement (Abdulkareem et al., 2022; DeLone & McLean, 2003). However, the perception of net benefit is not universal; it depends on individual expectations and prior experiences. For instance, a platform that reduces bureaucratic hurdles and empowers users to provide feedback may be beneficial, but only if these features are accessible and visible to users. If users fail to perceive a clear return on their effort, even a technically robust system may fail to drive participation intentions. It highlights a critical gap in many e-government implementations, where technical efficiency is prioritised over the perceived value delivered to citizens (Mishra & Shah, 2023; Seddon, 1997). Hence, this study proposed the following hypothesis.

H7: NB have a significant positive effect on EPI among e-government users.

Impact of TR on EPI

TR is a key factor in citizens' willingness to use e-participation platforms. It consists of two aspects: TR in the government's intentions and TR in the technologies used to deliver e-services (Li, 2021). When citizens perceive the government as transparent, accountable, and committed to addressing their concerns, they are more likely to participate in e-governance initiatives. Similarly, TR in the technology, such as its reliability, security, and data privacy, plays a pivotal role in fostering EPI (Abdulkareem et al., 2022; Gefen, 2003). Research has consistently shown that this construct is a critical predictor of behavioural intentions, including in the context of e-participation (Carter et al., 2011; Li, 2021; Nourallah et al., 2022). Citizens who TR the e-government platform are more likely to perceive their participation as meaningful and impactful, thus reinforcing their intention to engage (Mishra & Shah, 2023; Venkatesh et al., 2012). Conversely, a lack of TR can lead to disengagement, scepticism, and even resistance to e-governance initiatives. Thus, this hypothesis is put forward.

H8: TR has a significant positive effect on EPI among e-government users.

Impact of AN on EPI

Most e-government services and websites require users to be identifiable, including the enforcement of a real-name policy (Ruesch & Märker, 2012). It is mainly because the authority needs not just opinions but also information regarding the contributors to coherently orient executive action (Buccafurri et al., 2015). However, effective digital public management would consider the anonymity of the netizens as a vital element of virtual community engagement with the government (Halych & Demydkin, 2021). While previous studies present conflicting views on the Anonymity (AN) dimension, it appears to be crucial for encouraging e-participation through social media, particularly in situations where feedback or suggestions about government services are requested (Forestal & Philips, 2020). In these contexts, the value of participants' input outweighs the importance of their identities (Perbawani et al., 2018). In sum, AN is proposed as influential in the context of e-participation, and the following hypothesis is presented.

H9: AN has a significant positive effect on EPI among e-government users.

Impact of NT on EPI

NT is an ideology that prioritises the nation's interests (Bahna, 2019). It is also viewed as an internal sense of belonging that leads to the intention to contribute to the country's development. Citizens with a strong sense of nationalism would be eager to participate, provide suggestions, contribute ideas, or even comment on specific government initiatives (Poncian, 2021). Furthermore, with the rapid rise of web and Internet technologies, citizens nowadays are becoming more attached to their government. The net citizens, known as netizens, can easily reach the government through the platforms (Alarabiat et al., 2021). As a result, individuals with a higher sense of nationalism may be better equipped to engage with E-participation through social media. The preceding argument leads to the subsequent hypothesis.

H10: NT has a significant positive effect on EPI among e-government users.

Impact of US on EPI

US is a key driver of EPI, as satisfied users are more likely to continue engaging with e-government platforms and participate in governance processes. Satisfaction stems from positive experiences with the platform, including ease of use, service reliability, and the perceived quality of interactions. These experiences reinforce TR and create a sense of fulfilment, motivating users to transition from mere usage to active participation (DeLone & McLean, 2003; Venkatesh et al., 2012). When users find that e-government platforms meet their expectations, they are more inclined to participate in activities such as providing feedback, engaging in consultations, or accessing government services. This positive reinforcement strengthens their intention to engage further, as they perceive value in their participation. Conversely, dissatisfaction, arising from system inefficiencies or unmet expectations, can deter users from participating, as they may view the platform as untrustworthy or ineffective (Petter et al., 2008; Stefanovic et al., 2021). Moreover, US fosters emotional attachment and loyalty toward the platform, which amplifies participation intentions. Research has consistently shown that satisfied users are more likely to perceive their engagement as impactful and meaningful, leading to sustained participation. Satisfaction also acts as a mediating factor, bridging the gap between SYQ, SEQ, and EPI, highlighting its central role in shaping user behaviour (Tam & Oliveira, 2017). Based on this argument, this study hypothesised that:

H11: US has a significant positive effect on EPI among e-government users.

Impact of EPI on EPS

This study identifies EPI as a crucial factor influencing EPS. EPI reflects users' willingness and readiness to engage in e-government initiatives. Strong intentions to participate are crucial for transforming individual motivations into meaningful contributions, such as providing feedback, participating in consultations, or co-creating public policies. Research consistently shows that behavioural intentions are among the strongest predictors of actual behaviour, as per the TPB and the UTAUT (Ajzen, 1991; Venkatesh et al., 2003). When citizens express a high intention to engage, they are more likely to dedicate the time and effort necessary to participate meaningfully, thereby increasing the likelihood of successful outcomes. This alignment between intention and success emphasises the importance of fostering strong participation intentions as a precursor to achieving desired outcomes (Abdulkareem et al., 2022; Mishra & Shah, 2023). Therefore, the subsequent hypothesis is proposed.

H12: EPI has a significant positive effect on EPS among e-government users.

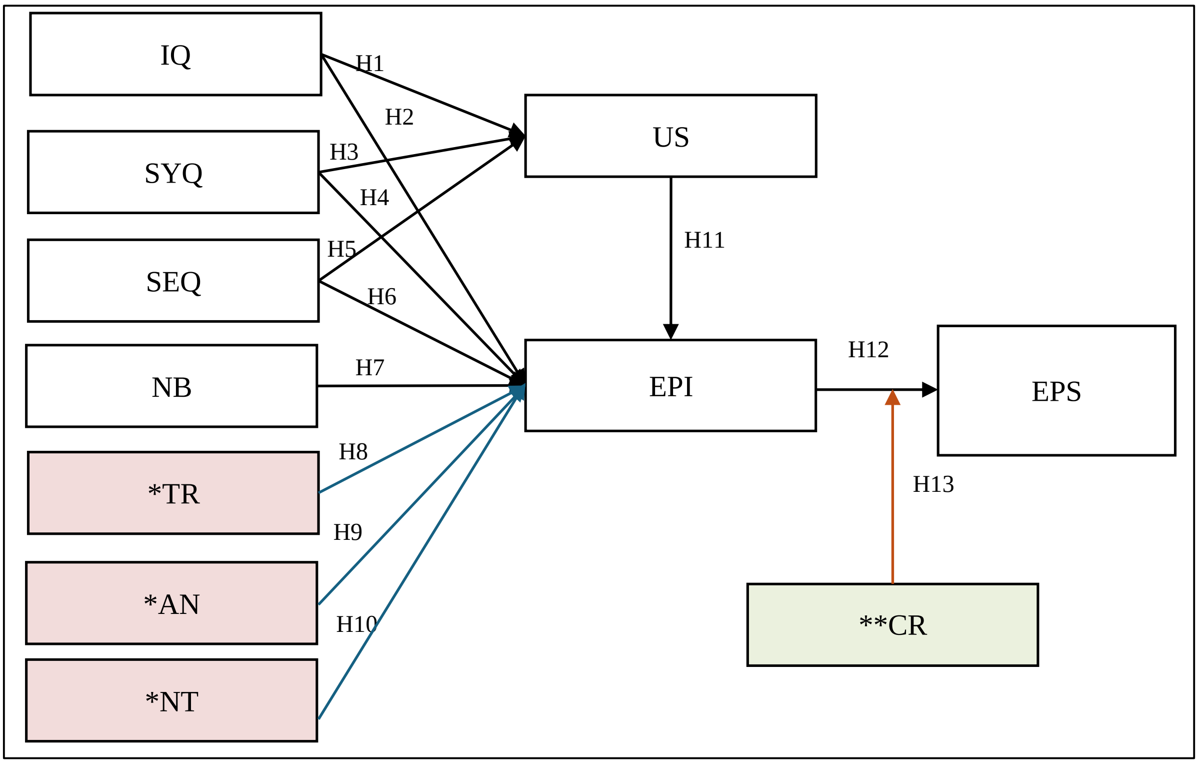
Moderating Role of CR in the Relationship between EPI and EPS

By shaping how societal norms and values influence the translation of intentions into impactful actions, this study noted that CR could moderate the relationship between EPI and EPS. While strong EPI may increase success in culturally supportive environments, this relationship can weaken in cultural settings where societal norms, values, or structural barriers hinder the effective realisation of participation outcomes (Tlaiss & Kauser, 2011). In collectivist cultures, the focus on shared objectives and group welfare amplifies the link between intention and success. Individuals are more likely to channel their participation intentions into meaningful actions if they perceive their contributions as benefiting the collective good or aligning with communal goals (Guo, 2023; Hofstede, 1997). Conversely, in individualist cultures, participation may be more fragmented, with individuals prioritising personal benefits over collective outcomes, which can dilute the overall success of e-participation initiatives (Ahangama & Krishnan, 2021). Furthermore, power distance and uncertainty avoidance significantly influence the relationship between intentions and participation in e-government platforms, with cultures characterised by low power distance and low uncertainty avoidance being more likely to translate intentions into successful engagement (Ahangama & Krishnan, 2021). While direct communication in low-context cultures facilitates this process, high-context cultures require platforms to adopt culturally sensitive designs. By aligning e-government initiatives with local cultural contexts, governments can enhance the effectiveness of participation and turn intentions into impactful actions. Therefore, this study proposed the following hypothesis.

H13: CR moderates the relationship between EPI and EPS among e-government users.

Figure 2

Research Model



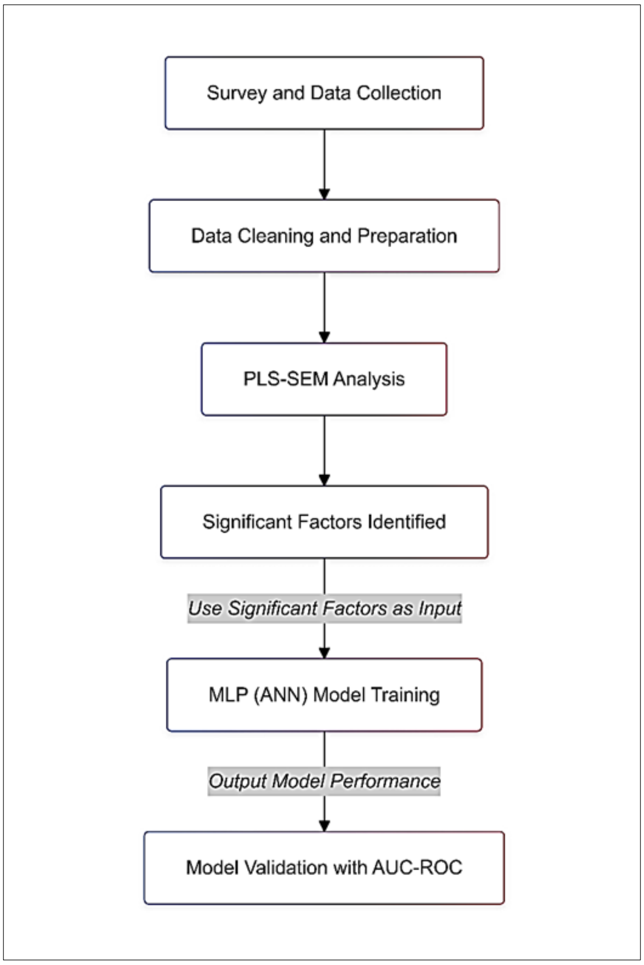
Notes. *new variables, **new moderator

METHODOLOGY

This study was conducted in several phases to ensure vigorous data collection, analysis, and validation. The process began with the development of a survey instrument and the collection of data using a purposive sampling procedure. The survey instrument underwent extensive validation procedures to confirm its reliability and relevance, including face validity, content validity, and a pilot study. Once data collection was completed, the dataset was cleaned and prepared for subsequent PLS-SEM and MLP/ANN analyses. Finally, the model's predictive performance was evaluated using the AUC-ROC. Figure 3 illustrates the research process of the study.

Figure 3

Research Process



Instrument Development and Data Collection

The survey instrument was developed to assess the relationships between quality dimensions, TR, satisfaction, and e-participation within the context of e-government in Malaysia. The items were adapted from validated sources (DeLone & McLean, 2003; Razmjoo et al., 2021) and were measured on a seven-point continuous scale. Before implementation, the instrument was reviewed by experts in IS, public administration, and management sciences to ensure content and face validity. A pilot study was conducted to confirm the reliability and clarity of the items before distributing the survey to the target population. Using purposive sampling, 450 questionnaires were distributed, and 428 valid responses were collected, exceeding the minimum sample size requirement of 115. Initial coding and preliminary analysis were conducted using SPSS Version 24, while SmartPLS 3.3 facilitated the PLS-SEM analysis.

PLS-SEM and MLP/ANN Analyses

PLS-SEM was employed as the primary analytical technique to test the theoretical model due to its flexibility and robustness. This method was chosen for its ability to handle small sample sizes, non-normal data distributions, and the estimation of both formative and reflective constructs (Hair, Sarstedt, et al., 2014). Compared to Covariance-Based SEM (CB-SEM), PLS-SEM excels in exploratory research contexts where theoretical development is ongoing, offering predictive insights that align well with technology adoption studies (Petter et al., 2008; Sofyani et al., 2020). The analysis was conducted in two stages: measurement model analysis to ensure reliability and validity (e.g., construct reliability, convergent validity, and discriminant validity) and structural model analysis to examine hypothesised relationships and the model's predictive power through R^2 values. The significant factors identified through PLS-SEM provided the foundation for subsequent analysis using ANN.

An ANN analysis was conducted to complement the findings of PLS-SEM, employing the MLP architecture. MLP was selected for its ability to model complex non-linear and linear relationships, making it particularly suitable for capturing interactions between the constructs identified in PLS-SEM. The MLP model was designed with two hidden layers, which enhance its learning capacity compared to single-layer architectures, allowing for greater depth and accuracy in prediction (Almarzouqi et al., 2022b). The ANN analysis used the significant predictors from the PLS-SEM as input variables, enabling the model to assess the relative importance of each predictor in determining EPS. The hybridisation aimed to balance predictive power, interpretability, and computational efficiency by using MLP, which helped overcome some of the limitations of PLS-SEM when faced with complex, non-linear interactions.

Model Validation

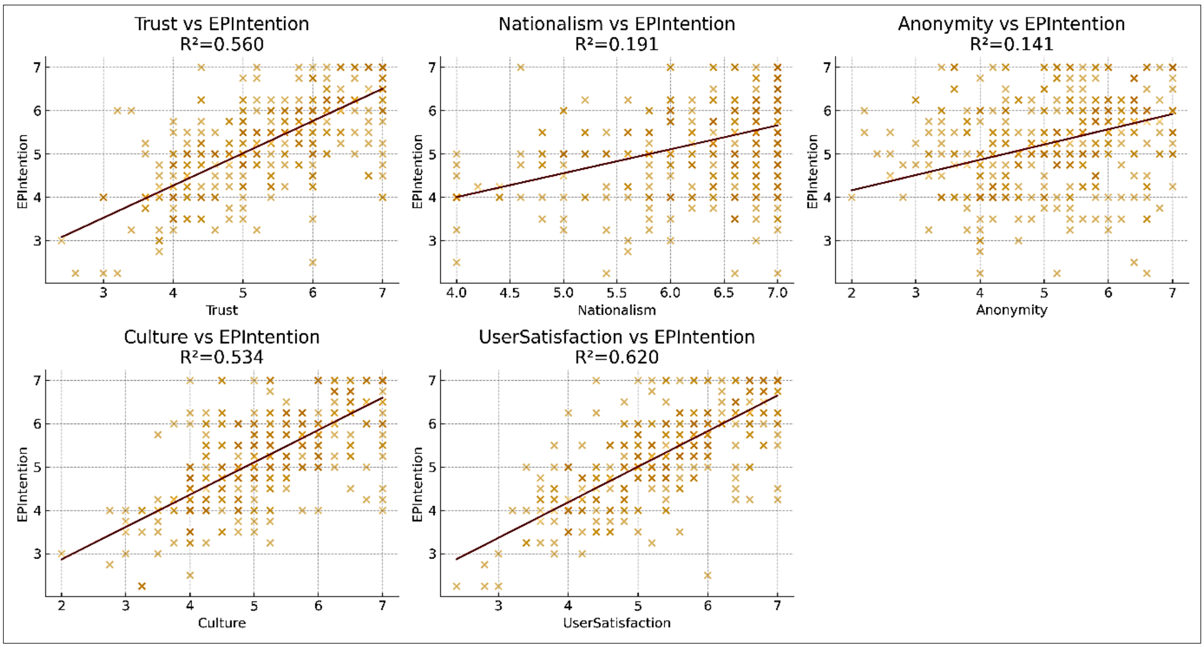
This study compared MLP with two other methods: the 5-Nearest Neighbours and Naive Bayes. The AUC-ROC metric is added to evaluate the model's ability to predict EPS, along with conventional threshold-dependent measures such as accuracy, precision, recall and F1-score. The incorporation of AUC-ROC ensured a robust evaluation of the hybrid framework's predictive capabilities, particularly in scenarios with class imbalance, thereby enhancing the study's reliability. In addition, the hybrid PLS-SEM and MLP approach was benchmarked against the individual PLS-SEM model using R^2 values.

ANALYSIS AND FINDINGS

Before the analysis, the data were cleaned and prepared. To examine the linearity of the data, scatterplot analysis was employed for each predictor against EPI, along with their corresponding R^2 values and fitted regression lines, as shown in Figure 4. It was found that some relationships are moderately linear, for example, between TR (R^2=0.560), CR (R^2=0.534) and EPI. On the other hand, other predictors, particularly NT (R2=0.191) and AN (R2=0.141), pose weak linearity towards EPI, indicating the existence of non-linear patterns. To confirm this, the Ramsey RESET test for non-linearity was applied, thus revealing strong evidence of non-linearity for AN ($F = 16.96$, $p < 0.001$), borderline evidence for NT ($F = 3.76$, $p = 0.053$), while no significant non-linearity was detected for TR ($F = 0.000$, $p = 0.989$), CR ($F = 2.266$, $p = 0.133$), and US ($F = 1.275$, $p = 0.259$). The existence of non-linear relationships, especially in AN, justifies the combination of PLS-SEM and MPL to handle non-linear data.

Figure 4

Scatterplot for Analysing the Linearity between Predictors and EPI



PLS-SEM

The proposed research model was initially analysed using PLS-SEM with SmartPLS software. PLS-SEM was conducted in two steps: measurement model validation and structural model testing. The measurement model includes validity and reliability assessments, utilising internal consistency and convergent and discriminant validity (Al-Fraihat et al., 2020). In this study, all composite reliability values exceeded the threshold value of 0.70 (ranging from 0.842 to 0.941), indicating acceptable internal reliability. The findings also demonstrated that each construct exhibited strong convergent validity, as indicated by AVE scores ranging from 0.615 to 0.828. Finally, the measurement also indicated good discriminant validity, with no HTMT value exceeding 1.0 (Henseler, 2017).

Next, PLS-SEM analysis was furthered to the structural model analysis stage. It began by investigating how the new constructs (TR, AN, NT, and CR) influence the changes in the predictive accuracy (R^2) value between the original and enhanced research models. By executing the PLS Algorithm in SmartPLS, the initial values of R^2 without the proposed new constructs are 0.805 for US (high), 0.620 for EPI (moderate) and 0.33 for EPS (weak). For the research model structural analysis (Figure 4), 13 hypotheses were examined. As indicated in Table 2, nine hypotheses (H1, H3, H4, H5, H6 and H8) exhibited a significant relationship, while the remaining four (H2, H7, H9 and H10) did not.

Table 2

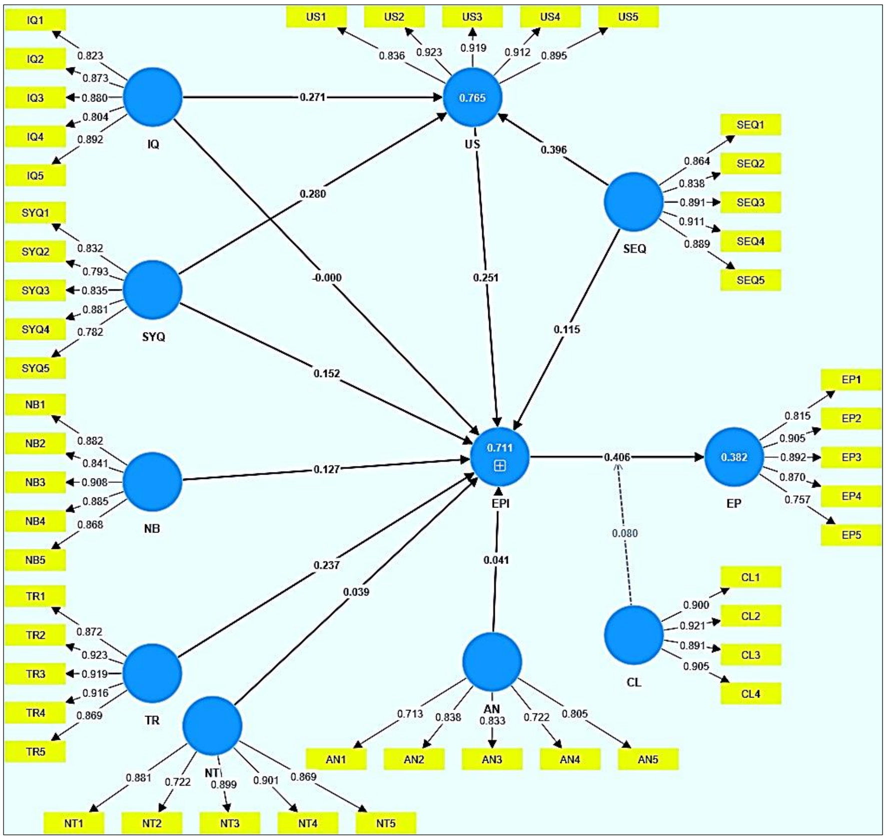
Structural Model Testing

Hypothesis & Relationship		ß	T Values	p Values	Decision
H1	IQ -> US	0.042	6.486	0. 000	Accepted
H2	IQ -> EPI	0.045	0.048	0.962	Rejected
H3	SYQ -> US	0.052	5.435	0. 000	Accepted
H4	SYQ -> EPI	0.059	2.596	0.009	Accepted
H5	SEQ -> US	0.051	7.695	0.000	Accepted
H6	SEQ -> EPI	0.062	1.937	0.053	Accepted
H7	NB -> EPI	0.068	1.836	0.066	Rejected
H8	TR -> EPI	0.054	4.390	0.000	Accepted
H9	AN -> EPI	0.034	1.232	0.218	Rejected
H10	NT -> EPI	0.041	0.950	0.342	Rejected
H11	US -> EPI	0.071	3.534	0.000	Accepted
H12	EPI -> EP	0.067	6.104	0.000	Accepted
H13	EPI -> CR -> EP	0.033	2.423	0.015	Accepted

In terms of predictive accuracy, Figure 5 reveals that the primary endogenous variable, EPS, achieved a moderate R^2 value of 0.345. The variables EPI and US also achieved moderate and high R^2 values, with EPI at 0.728 and US at 0.765.

Figure 5

Path Modelling

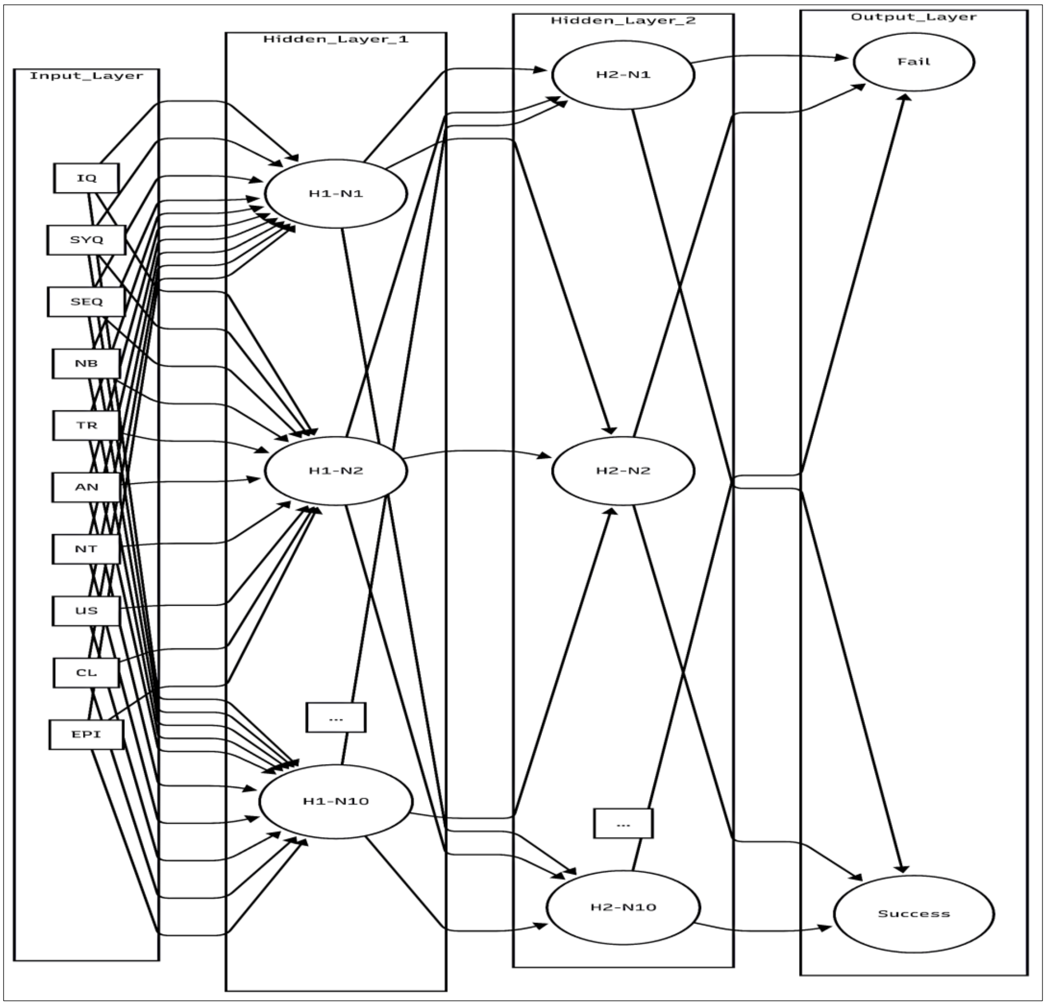


Artificial Neural Network Analysis Based on MLP Architecture

MLP, a type of ANN, is used in the second step of the analysis to complement the PLS-SEM findings and to highlight each predictor's factor-relevant importance. MLP has a higher prediction accuracy than SEM due to its capabilities for assessing both linear and non-linear relationships (Almarzouqi et al., 2022b). The MLP analysis consists of inputs, hidden layers, and outputs. Following the recommendation of previous studies, two hidden layers were employed for the MLP (Almarzouqi et al., 2022b). Using two hidden layers enables the MLP model to learn more deeply for the output neuron node (Alharbi & Sohaib, 2021). The MLP model uses the ReLU function as the activation function for the hidden neurons and the Sigmoid function for the output neuron. Moreover, the range between 0 and 1 for both input and output neurons is normalised to enhance the MLP model's performance. The MLP model has ten input factors (significant predictors tested in PLS-SEM analysis): IQ, SYQ, SEQ, NB, TR, AN, NT, US, CR and EPI, while the output is an EPS. Figure 6 illustrates the MLP model used in this work.

Figure 6

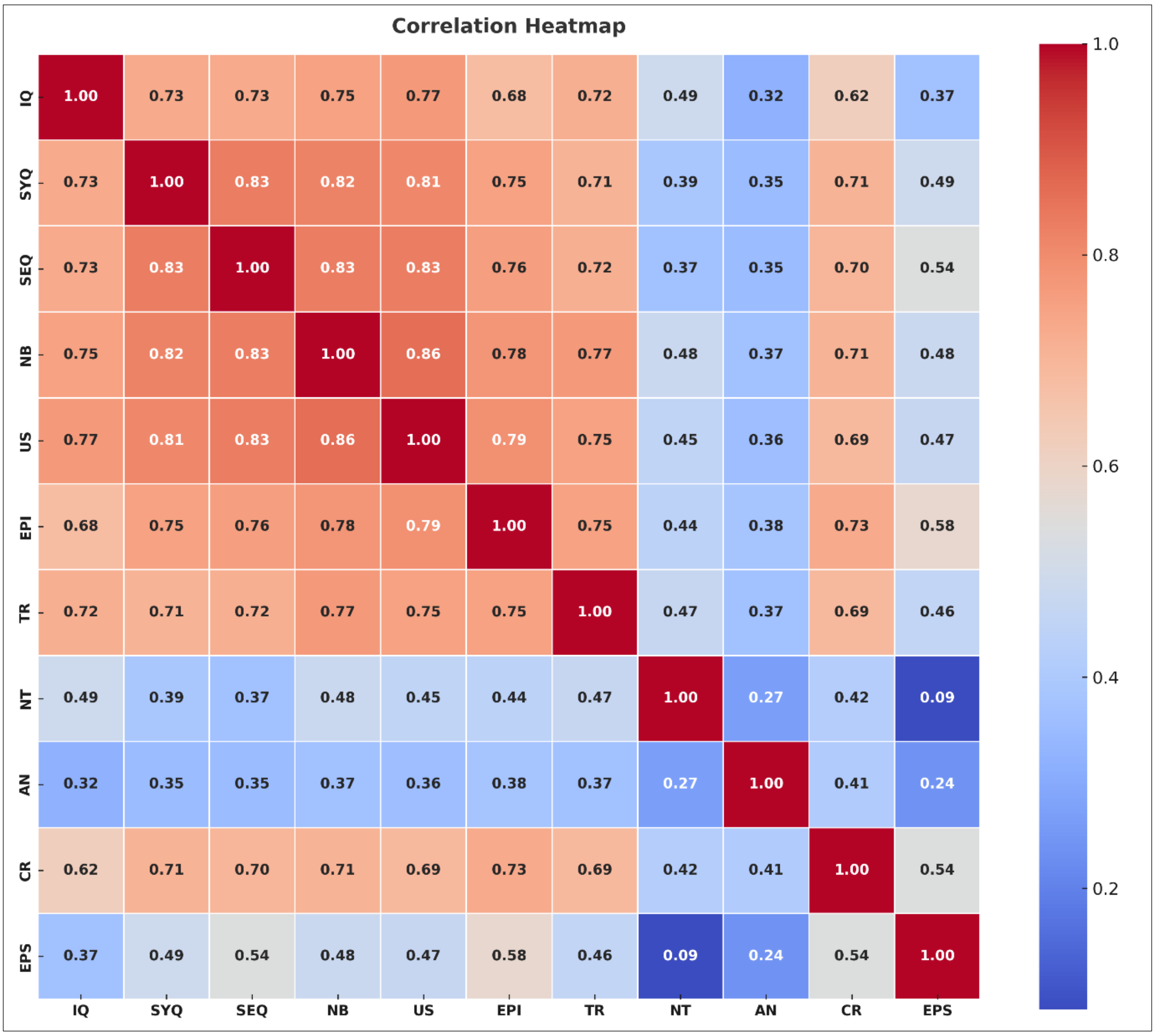
Structure of the MLP Model



The first step is to gain insight into which factors are positively or negatively correlated, thereby aiding in the interpretation of the model's predictions. This study utilised correlation heatmaps to examine the relationships between variables in a dataset. Figure 7 shows the values indicating highly correlated factors suitable for building and training neural network models. This study employed an MLP architecture with sigmoid activation for the hidden layers and SoftMax for the output layer, which is a standard setup for MLPs used in classification tasks (Almarzouqi et al., 2022b). It's important to fine-tune hyperparameters, monitor training/validation performance, and introduce regularisation to achieve a well-performing model. The input layer consists of nodes (neurons) representing the features of your dataset, such as SYQ, IQ, and SEQ. Each node in the input layer corresponds to a feature (Almarzouqi et al., 2022b). The values from the input layer are fed forward to the hidden layers.

Figure 7

Correlation Heatmap



In this study, an MLP model with two hidden layers was used. Each hidden layer consists of 10 neurons, with sigmoid activation functions applied to introduce non-linearity and enable the network to learn complex patterns. The output layer, designed for a binary classification task (success or failure), uses the SoftMax activation function to produce a probability distribution over the two classes. The model, illustrated in Figure 4, was trained using an appropriate optimisation algorithm such as stochastic gradient descent and a binary cross-entropy loss function. Network parameters were updated iteratively using backpropagation, which calculates gradients and adjusts weights and biases to minimise the loss over training batches.

Model Validation

In the first validation stage, this study assessed the model on a separate validation set to evaluate its generalisation performance. The dataset was split into 80% for training and 20% for testing, ensuring a robust evaluation framework. The performance of the MLP was measured using widely accepted classification metrics, namely accuracy, precision, recall, and the F1 Score (Alshboul et al., 2022), against several machine learning classifiers, such as 3-Nearest Neighbours, 5-Nearest Neighbours, Naive Bayes, and Logistic Regression.

Table 3 presents the classification results of the evaluated machine learning classifiers. The Neural Network achieves higher values across all metrics, indicating superior predictive accuracy compared to the other classifiers. The model's overall accuracy of 90.1% indicates that it correctly predicts the majority of instances. The high-precision values demonstrate its effectiveness in minimising false positives. The strong F1 score, which balances precision and recall, further confirms the model's well-rounded performance.

Table 3

Comparison of Classification Results across Machine Learning Classifiers

Machine Learning Classifier	Accuracy	F1	Precision	Recall
Logistic Regression	0.8222	0.8737	0.8406	0.9095
Naive Bayes	0.6793	0.7418	0.8144	0.6810
kNN (3)	0.8513	0.8994	0.8291	0.9828
kNN (5)	0.8076	0.8740	0.7842	0.9871
Neural Network	0.9009	0.9283	0.9091	0.9483

In this study, a confusion matrix was used to evaluate the performance of an ANN model (Figure 8). The matrix summarised the number of correct and incorrect predictions on a dataset. It categorises predictions into four types: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Based on the metrics (accuracy, precision, recall, and F1 score), the model performs well, particularly in correctly identifying both positive and negative instances.

Figure 8

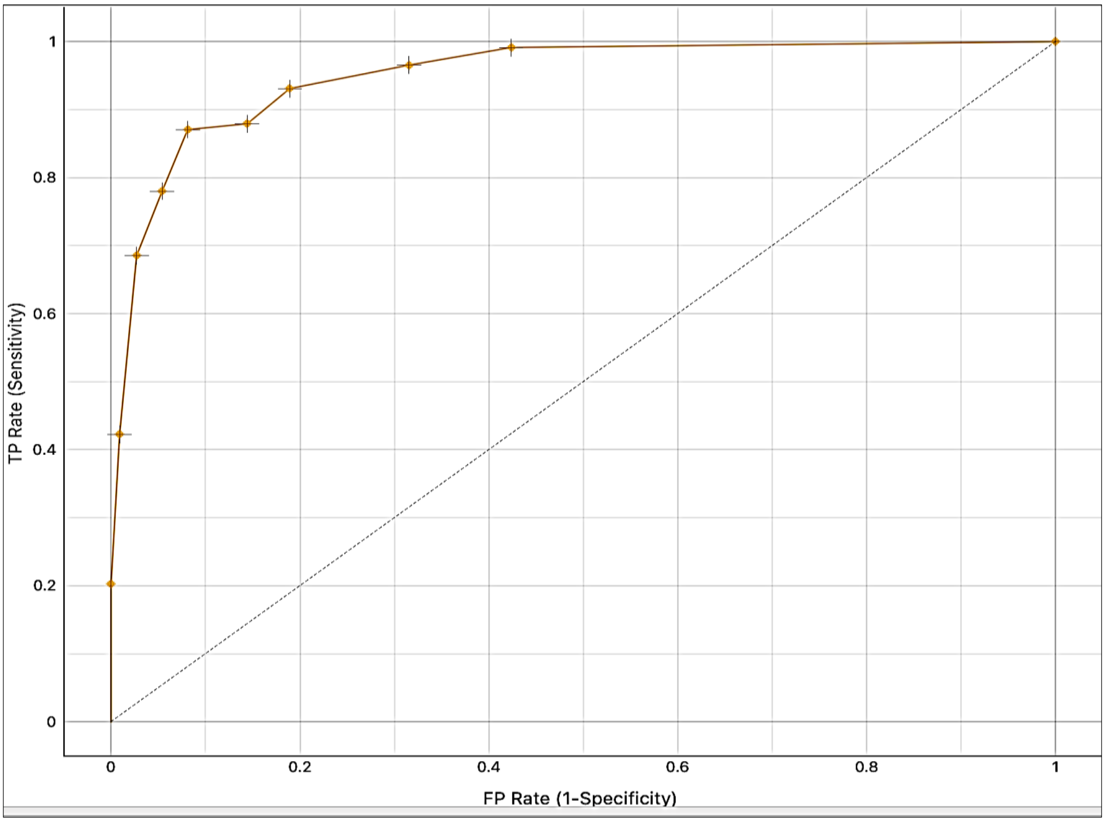
Confusion Matrix

		Predicted		
		No	**Yes**	**Total**
Actual	**No**	48	63	111
	Yes	3	229	232
	Total	51	292	343

To validate the MLP model, the AUC-ROC metric was used. The model achieved an AUC-ROC value of 0.955, showing a strong ability to distinguish between the two classes: fail and success (e-participation). The ROC curve (Figure 9), which illustrates the trade-off between sensitivity and specificity at various thresholds, exhibits a steep rise, indicating good model performance.

Figure 9

ROC Curve



The findings from the accuracy, precision, recall, and F1 Score metrics, combined with the AUC-ROC analysis and confusion matrix, demonstrate the MLP model's robustness and reliability in predicting e-participation. Overall, the model performs well and provides valuable insights for understanding and predicting e-participation outcomes. Finally, the prediction of e-participation is made in the final stage of the analysis by calculating a composite score from five items (EP1 to EP5). The scores were averaged to derive an EPS score, and respondents were categorised into two groups: success (score ≥ 4) and non-success (score < 4), as shown in Table 4. This binary classification provides insights into the effectiveness of the e-government platform and the level of engagement among participants. As shown in Table 4, the e-government platform has a high success rate of 90.10%, indicating strong user participation and satisfaction with the platform's features and services.

Table 4

Prediction of EPS Summary

Category	Prediction Count/Actual	Percentage (%)
Success (Score ≥ 4)	220/232	94.80
Non-Success (Score < 4)	89/111	80.20

For completeness, this study also compared the MLP model with several other machine learning classifiers, such as 3-Nearest Neighbours and Naive Bayes. Table 5 describes the classification performance of the compared classifiers.

Table 5

Classification Performance of the Compared Classifiers

Classifier	Accuracy	Precision	Recall	F1 Score	AUC-ROC
MLP (This study)	0.901	0.909	0.948	0.928	0.955
5-Neareast Neighbours	0.808	0.784	0.987	0.874	0.902
Naïve Bayes	0.679	0.814	0.681	0.742	0.709

As shown in Table 5, our MLP model outperforms the other classifiers across all performance metrics. It achieves the highest accuracy (0.901), precision (0.909), recall (0.948), F1 score (0.928), and AUC-ROC (0.955), indicating strong overall performance and excellent ability to distinguish between the two classes. The 5-Nearest Neighbours (5-NN) classifier demonstrates high recall (0.987), suggesting that it correctly identifies most of the successful cases. However, it has lower precision (0.784), indicating a higher rate of false positives compared to the MLP model. This trade-off results in a lower F1 score (0.874) and AUC-ROC (0.902). Naive Bayes shows the lowest performance among the three models, with an accuracy of 0.679 and a relatively low recall (0.681), suggesting it struggles to identify positive cases correctly. Despite having a relatively high precision (0.814), the imbalance between precision and recall results in a moderate F1 score (0.742) and AUC-ROC (0.709). These comparisons confirm that the MLP model is the most robust and reliable classifier for predicting EPS in this study.

DISCUSSION

The main contributions of this study are in two aspects. First, theoretically, it was demonstrated that the extension of D&M by incorporating new constructs, such as TR, AN, NT, and CR, has enhanced the model's predictive accuracy, as shown in Table 6. It can be observed that EPI shows the most significant improvement, with R^2 rising from 0.620 to 0.728. It highlights the role of constructs like TR and NT, which were added to the enhanced model. These variables account for a substantial portion of the variance in users' intentions to participate in e-government. Furthermore, it can be observed that the R^2 for EPS shows a marginal increase from 0.330 to 0.345. While the improvement is minor, it demonstrates the influence of the cultural factor (CR) on successful e-participation. For the US, the R^2 shows stability, indicating that the new constructs do not diminish the model's ability to explain satisfaction but strengthen the relationships leading to EPI and EPS.

Table 6

Summary of Predictive Accuracy Enhancement in the Research Model

Construct	Initial R^2	Enhanced R^2	Change
US	0.805 (High)	0.765 (High)	-0.04
EPI	0.620 (Moderate)	0.728 (Moderate)	+0.108
EPS	0.330 (Weak)	0.345 (Weak)	+0.015

Second, this study has extended the model validation by incorporating AUC-ROC for EPS prediction. While previous studies have been done on hybridisation between PLS-SEM and MLP, this study found that most of them lack robust model evaluation. Moreover, in the case of EPS, predicting both success and non-success will provide vital insights to decision-makers and, thus, must be included. As a result, this AUC-ROC has yielded two critical insights: model accuracy and success prediction. In terms of model accuracy, the AUC-ROC score of 0.955 is substantial to validate the model's robustness and ability to predict EPS. Similarly, the prediction of 94.80% success could be a valuable insight for policymakers. It shows that while the implementation of e-participation is on the right path, there is nothing to worry about if the government is ready to improve in specific aspects, such as information SYQ, TR, and transparency.

CONCLUSION

In sum, this study has contributed to the body of knowledge in e-participation research in three aspects. Theoretically, by integrating socio-cultural constructs, this study has enhanced the explanatory power of D&M, as evidenced by the increase in R^2 values of the endogenous constructs. Furthermore, this study also contributed methodologically by combining PLS-SEM with MLP and validating the model using robust classification metrics and model comparisons. Lastly, the study offers practical predictive insights for governments and policymakers to foster inclusive and culturally aligned e-participation. Through this study, it is empirically demonstrated that governments worldwide should recognise that EPS is driven not only by technological aspects but also by socio-cultural and TR-related factors.

Although this study provides valuable insights into EPS, it still has several limitations that could be useful for future work. First, data were collected solely from students, which may introduce bias and limit the generalisability of the findings to other populations. Moreover, the focus on a single country restricts applicability across different cultural and socio-political contexts. Additionally, the selection of thresholds in the R^2 and AUC-ROC analyses could lead to different interpretations of success rates. Finally, the study's cross-sectional design does not consider changes in user behaviour or attitudes toward e-participation over time, particularly as e-government technologies evolve.

On the positive side, these limitations provide interesting avenues for future research. Future research in e-participation should focus on including diverse and representative samples, incorporating various demographics, such as professionals and citizens from urban and rural areas, to enhance generalisability. Expanding studies internationally, particularly within Southeast Asia, can validate the model across different socio-cultural contexts and illuminate the impacts of TR and CR on EPS. Investigating the variance of MLP parameters will offer insights into their predictive capabilities. Longitudinal studies could capture shifts in user behaviour and participation dynamics in response to evolving e-government services. Additionally, exploring context-specific constructs, experimenting with optimal thresholds for classification tasks, and combining self-reported and actual behavioural data will further refine the evaluation of EPS.

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