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Evaluating Egyptian citizens' perception toward introducing voice assistant technology as a means of improving public service delivery: utilizing machine learning as an additional perception's predictor

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Abstract

Purpose This research assesses the inclination of Egyptian citizens toward embracing Voice Assistant Technology (VAT) to deliver public services based on the functioning of perceived usefulness, ease of use, trust, and perceived risk. This also examines the possibility of using machine learning (ML) models to forecast adoption behavior.

Design/methodology/approach A mixed-method design was applied, supplementing survey data from 398 participants with qualitative analyses of expert interviews. An extended Technology Acceptance Model (TAM) incorporating trustworthiness and perceived risk was employed. Additionally, ten (ML) algorithms were applied to predict acceptance by citizens.

Findings Helpful conclusions were reached, the most helpful being that usefulness, ease of use, and trust highly and positively affect (VAT) acceptance while perceived risk highly and negatively affects VAT acceptance. (ML) analysis validated these findings with Stochastic Gradient Descent (71.9% accuracy) and Ridge Regression (70.9%) as the best predictors, yet Decision Tree was poor (49.3%). These conclusions indicate that risk perceptions need to be addressed and trust enhanced to facilitate VAT adoption in developing-country contexts.

Originality/value This paper contributes to the field by extending TAM with trust and risk factors and adding ML predictive modeling to public administration studies. The results provide policy practitioners and technologists with actionable advice on how to incentivize AI-enabled public service delivery via citizen-focused, trust-building approaches.

Keywords Public service delivery, Public administration reform, Voice assistant technology (VAT), Technology acceptance model (TAM), Using AI in predicting citizens' attitude

Introduction

Thoughts, sentiments, and behaviors of citizens toward public provision of service are building blocks of social and behavioral sciences [9, 44, 62]. They impact the choice-making of citizens toward interacting with accessible products and services. Perception of citizens regarding (VAT) to ease service delivery is one research area that is gaining pace. (VAT) has grown in scholarly and

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real-world interest over time, especially with the development of artificial intelligence (AI) that includes (VAT) and (ML) technology [58]. These technologies work using voice command on people's phones and computers, allowing more human-like interaction [37]. For instance, Rolandsson (49) stated that a little over 50% of Google searches are done using voice and between the years 2015 and 2019, in the US alone, more than 27 million devices such as Google Home and Amazon Alexa were sold. The sector envisions voice assistants having a greater contribution to everyday chores such as hotel reservation, appointment booking in medical clinics, and online shopping.

Machine learning-driven virtual assistants are programmed to identify and perform voice commands, offering services ranging from weather forecasts to online shopping. Their functions keep broadening as they find their way on smartphones, smart speakers, wearables, and smart TVs [34]. Despite all this worldwide coverage, however, not much is known about what drives the uptake and usage of these technologies by citizens, especially in the developing world and generally in government. This knowledge gap is substantial, with governments becoming more interested in using AI-based assistants to improve the delivery of services.

Current studies of AI-based virtual assistants and e-government services have been at times limited to small samples and narrow populations, and thus, results' generalizability is not certain. Sameh et al. [51], Susanto and Aljoza [56] emphasized examining how to promote e-government service acceptance. Other research [15, 33, 40, 41, 50] has considered psychological determinants that stimulate e-government adoption, and personal acceptance is also influenced by attitudes, social influence, and beliefs toward the technology and service provider. Most of the earlier studies, however, utilized fundamental adoption measures with major emphasis on perceived ease of use and perceived usefulness [28].

This creates an evident gap in research: There are not many empirical tests of other variables such as trustworthiness and perceived risk, yet these are precisely the variables most core in determining citizens' intention to use e-government systems in high-uncertainty environments like Egypt. Furthermore, even though the (TAM) [2, 13] is dominant, it has scarcely been adapted to include such culture-sensitive variables in developing nations. The second methodological shortcoming occurs because earlier studies of public administration rarely integrate behavioral adoption theories with (ML) processes, which can generate better predictions and policy-oriented conclusions.

To fill these shortcomings, the current study investigates Egyptian citizens' attitude toward (VAT) adoption in the provision of public services. It explores whether perceived usefulness, ease of use, trust, and perceived risk affect acceptance. A mixed-method study is used, combining quantitative survey information from the citizen and qualitative information from expert interviews. Moreover, ML predictive models and regression analysis are used in the current study to evaluate the trend of adoption and to test the conceptual model. Two research questions guide the current study: (1) What drives citizens' adoption of AI-based virtual assistants? and (2) How can citizens be enticed to adopt and utilize AI-driven virtual assistants in public service delivery with convenience?

Literature review

An overview

Use and dissemination of information have ever been at the core of economic and institutional development, defining market power, leadership, and value creation. Information economics has traditionally focused on how information affects economic systems and governance mechanisms. In the era of technology in the digital age, this relationship has been transformed with organizational and governmental action making possible enhanced efficiency, responsiveness, and stakeholder engagement. Governments are becoming more interested in technology in order to achieve optimal citizens' satisfaction and government trust [19, 23, 48]. Success also depends on end users' viewpoints and adoption [12, 20, 30, 57, 60].

(AI) and (ML) have been leading these changes, opening up possibilities in the public and private sector [47]. The global market for AI would grow to $190 billion by 2025 and over $500 billion of investment by 2024 [31]. In government administration, AI and ML allow governments to manage vast datasets in a better way, predict problems, and enhance the delivery of services [6, 59]. Adoption is slower in developing environments due to infrastructural limitations, resistance to change in culture, and inadequate digital literacy [3, 4, 41].

(VAT) is one of the fastest-growing AI technologies, from Siri in 2010 to widely used in Google Assistant, Alexa, and Cortana today [1]. These technologies respond to human requests after understanding natural language [8, 63], revolutionizing human–computer interaction with convenience, inclusiveness, and symbolic value [36, 53]. While rapid adoption in developed economies, to date, there is little evidence regarding (VAT) adoption for developing nations, especially in e-government environments, where cultural aspects, trust, and risk behaviors are of primary importance [15, 25, 26, 29, 40].

Hypothesis development

(TAM) is shown by [13, 14] as the most common model of user acceptance of innovations, wherein Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are identified as determinants of behavioral intention [11, 38, 39]. PU refers to the degree to which users believe technology enhances performance, whereas PEU refers to little effort perceptions. Empirical data always favor their positive influence on adoption [33].

But (TAM) cannot be exhaustive in explaining e-government service adoption. Researchers stress the significance of Trustworthiness and Perceived Risk [22, 64]. Trustworthiness includes competence (system effectiveness), honesty (open communication), and benevolence (real concern for users). Trust is especially crucial in high-uncertainty avoidance countries like Egypt whose people are inherently paranoid of new technology [26, 29]. Perceived Risk, however, reflects anxieties over privacy, fraud, and dependability [5, 17]. Cybercrime has generated greater distrust and rendered building trust a pre-adoption necessity [52].

Demographics are also included. Youths such as Millennials and Gen Z would be likely to be early adopters based on digital literacy and usability desire. CAPMAS (2018) indicates that 21% of the population are youths of age 18–29 with 47.4% Internet users and 84.5% mobile phone users. Generation differences hence establish acceptance. In addition, social identity and symbolic motivations drive adoption because technology adoption becomes a status symbol [36]. All these reasons serve as the foundation of the following hypotheses:

- H1: Perceived Usefulness positively affects citizens' acceptance of (VAT).
- H2: Perceived Ease of Use has a positive effect on citizens' acceptance of (VAT).
- H3: Trustworthiness has a positive effect on citizens' acceptance of (VAT).
- H4: Perceived Risk has a negative effect on citizens' acceptance of (VAT).

Conceptual model

This research constructs a theoretical model (Fig. 1) that combines TAM's original parameters (PU and PEU) with Trustworthiness and Perceived Risk to predict (VAT) acceptance by Egyptian citizens in the nation's public services. The model suggests functional determinants and socio-cultural determinants of technology acceptance. While (TAM) addresses root determinants, supplementing it with trust and risk places adoption in developing nations with infrastructural constraints, privacy issues, and uncertainty avoidance cultural values [3, 4, 15, 40].

By situating TAM in the Egyptian e-government context, this study fills the empirical lacuna of AI-facilitated adoption in emerging economies. It contributes to theory—by placing (TAM) extensions in an environment—and practice as it provides policymakers with a framework to develop citizen-centered digital transformation policies.

The research utilized an extended (TAM) model that included two extra variables: trust and perceived risk. The said statistical testing was utilized to test the model and develop a robust analysis of citizens' attitudes toward (VAT). By juxtaposing both the quantitative and qualitative approaches, this research offers a holistic evaluation of Egyptian citizens' attitudes toward (VAT) application in public service provision.

Research methodology

This research utilizes a mixed-method design, in which qualitative and quantitative data are integrated together to assess the attitudes of Egyptian citizens toward the use of (VAT) in the provision of public services. The design improves breadth as well as depth of information as it assesses the attitudes of the citizens based on guided questionnaires and experts' views based on interviews. (ML) predictive analysis was also utilized to forecast adoption behaviors and enhance analytical rigor [42].

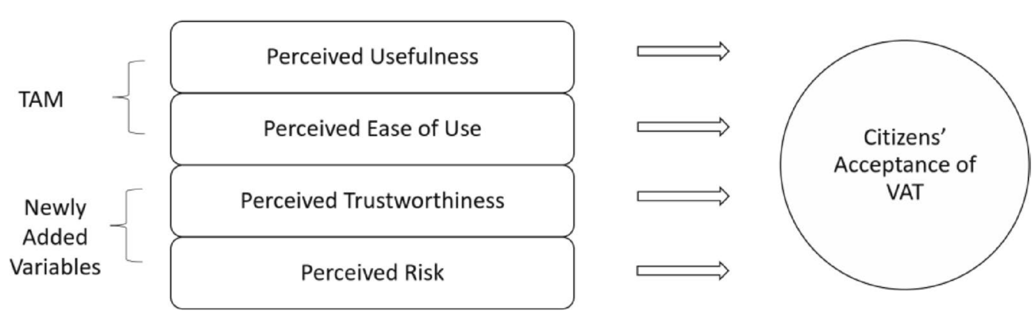

Fig. 1 Conceptual model

Data collection

Secondary data were accessed from textbooks, peer-reviewed journals, and online databases in order to determine the research gap and set research objectives and questions. Primary data were gathered using two sources:

1. Systematic questionnaire to Egyptian citizens applying for or availing government public services.
2. Expert semi-structured interviews with individuals from the telecom and software industry.

This mixed method made both user experience and technical feasibility aspects of VAT catered to.

Data collection instruments' design

The survey instrument consisted of 27 items on five dimensions, with each dimension capturing the four independent variables (ease of use, perceived usefulness, trustworthiness, and perceived risk) and one dependent variable (citizen acceptance). Perceived usefulness and ease of use constructs were adapted from (TAM) [13], with additions on trustworthiness and perceived risk being made (Gefen et al. 2003; [18]).

Instrument validation was conducted in line with best practices:

- The items were pre-tested with 30 respondents to ensure they were understandable and clear.
- Content validity was ensured by three researchers and two practitioners.
- Cronbach's alpha ($\alpha \geq 0.70$ for constructs) was used to test reliability.
- Exploratory Factor Analysis (EFA) was employed in quantifying the constructs' dimensionality [55].
- Furthermore, Confirmatory Factor Analysis (CFA) via AMOS v24 was utilized to ascertain construct validity. Average Variance Extracted (AVE), factor loadings, and measures of discriminant validity were used to establish the measurement model's strength.

The semi-structured interview plan was to gather information from coding engineers of software firms and WE (Egypt National Telecommunication Company) engineers regarding the possibility, coding necessity, and security issues of (VAT) in public service provisioning.

Sampling

Non-probability convenience sampling method was used considering availability and economic constraints. Target respondents were technologically literate high school and university students, public and private sector workers, and entrepreneurs for the questionnaire. Google Forms were used to distribute the Internet-based questionnaire, and 398 usable responses were gathered.

Concurrently, 14 interviews were held with experts: five with (VAT) coding engineers and software solution programmers, and nine with WE Egypt maintenance engineers. Convenience sampling gave handy practice but possibly restricted generalizability of findings, and this deficiency is recognized [16].

Data analysis

Quantitative analysis

Survey responses were analyzed using a number of statistical methods:

- *Descriptive statistics* yielded demographic information such as gender, age, income, and education.
- *Internal consistency* through Cronbach's alpha showed high internal consistency for all the constructs ($\alpha > 0.7$).
- *Construct validity* was established through Exploratory and Confirmatory Factor Analysis (EFA & CFA). CFA was run in AMOS v24, which tested model fit indices such as CFI, TLI, and RMSEA. Model fit indices indicated acceptable construct validity: $\chi^2/df = 2.10$, Comparative Fit Index (CFI) = 0.94, Tucker–Lewis Index (TLI) = 0.93, and Root-Mean-Square Error of Approximation (RMSEA) = 0.056. These values are within recommended thresholds (Hu and Bentler 27), supporting the adequacy of the measurement model.
- *Regression analysis* using SPSS v28 was used to determine the impact of perceived ease of use, perceived usefulness, trust, and perceived risk on VAT acceptance by citizens. SPSS is chosen due to its suitability for survey-based hypothesis testing in social sciences [21].
- *Machine learning models* Predictive modeling was performed using Python (Scikit-learn library), which demonstrates a rich set of algorithms for application and comparison. The ten ML algorithms, such as Logistic Regression, Ridge Regression, Stochastic Gradient Descent, Random Forest, Decision Tree, Gradient Boosting, Support Vector Machine, K-Nearest Neighbors, Naïve Bayes, and Multi-Layer Perceptron, were tested. Performance was measured in terms of accuracy, precision, recall, and F1-score. Stochastic Gradient Descent (71.9%) and Ridge Regression (70.9%) recorded the highest prediction accuracy and Decision Tree (49.3%) the worst [43, 54].

Qualitative analysis

Interview transcripts were coded and interpreted using thematic analysis and yielded overarching themes of user trust, perceived risk, and infrastructure preparedness. Results were applied to contextualize and inform survey findings as per the convergent parallel mixed-methods approach [42].

Integration of findings

Quantitative and qualitative data were combined at the point of interpretation to cross-validate findings. For example, survey data on the importance of trust were complemented with expert apprehensions regarding coding security and transparency, while regression results establishing perceived risk and low use were complemented by experts referring to citizens' fear of fraud [42].

Results and discussion

Demographics characteristics

According to Fig. 2, the sample unit represents a total of 398 respondents. There is a balanced gender distribution which minimizes the stereotyped bias associated with male preference to deal with technology. There is a relatively even distribution across age groups, with a slight concentration in the younger (<25) and older (>45) categories. This diversity supports a broad understanding of perspectives across different life stages. It was intended that the questionnaire would target technology-oriented individuals. The high number of university and postgraduate individuals (over 70%) indicates an educated sample. The large percentage of unemployed individuals (33.7%) can be merely tracked down to student population. However, alongside private sector employees suggest a mixed economic engagement, potentially providing insights into views from both employed and unemployed perspectives. In conclusion, this demographic diversity across gender, age, education, and occupation suggests a well-rounded sample, which may support balanced insights across these characteristics.

A reliability test represented in Cronbach's alpha was also conducted. Table 1 represents the output.

According to Table 1, the five variables' Cronbach's alpha is ≥ 0.857 indicating a high level of reliability and consistency of all the questions representing the variables.

Table 1 Cronbach's alpha test for reliability

Variable	N of items	Cronbach's alpha
Usefulness of VAT	8	0.905
Ease of use of VAT	5	0.857
Trustworthiness of VAT	4	0.866
Perceived risk of VAT	5	0.889
Citizens' perception toward VAT represented in their acceptance of the technology	5	0.928

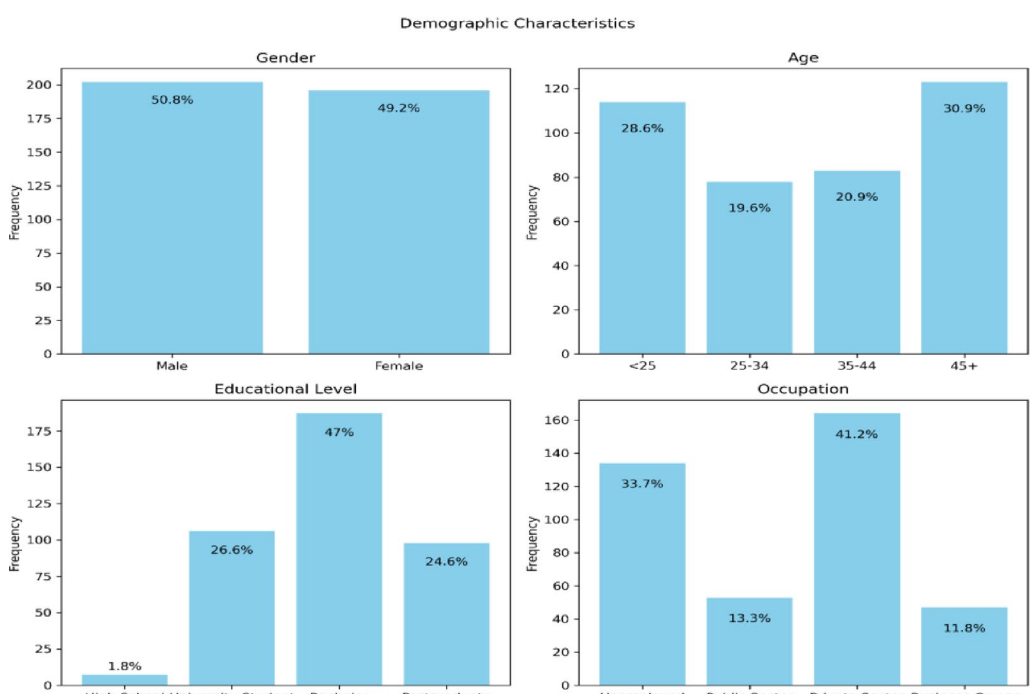

Fig. 2 Demographic characteristics distribution

Measurement model validation

CFA results demonstrated strong construct validity. All standardized factor loadings exceeded 0.70, and AVE values were above 0.50, confirming convergent validity. Discriminant validity was established as the square root of each construct's AVE exceeded inter-construct correlations. Model fit statistics were satisfactory (χ^2/df = 2.10, CFI = 0.94, TLI = 0.93, and RMSEA = 0.056), further confirming the robustness of the measurement model.

It was necessary to conduct a factor analysis test to identify underlying relationships between variables by grouping them into factors based on shared variance. The purpose of this technique is to simplify data by reducing a large number of variables into a smaller, interpretable set of factors. Results are shown in Table 2.

Table 2 shows that KMO values range from 0 to 1. A KMO of 0.6 or above is generally considered acceptable; values closer to 1 indicate better adequacy for factor analysis. In summary, all dimensions have strong KMOs, supporting the use of factor analysis to explore these aspects of VAT perceptions (Table 3).

A multiple linear regression test was conducted. It was necessary to understand how each of the independent variables (Perceived Usefulness, Perceived Ease of Use, Perceived Trustworthiness, and Perceived Risk) contributes to the outcome via the presence of the coefficients.

Table 2 Kaiser–Meyer–Olkin (KMO) for factor analysis

Variable	KMO
Perceived usefulness of VAT	0.905
Perceived ease of use of VAT	0.836
Perceived trustworthiness of VAT	0.816
Perceived risk of VAT	0.783
Citizens' perception toward VAT represented in their acceptance of the technology	0.881

Determinants of Egyptian citizens' perception toward introducing VAT: empirical model

The Egyptian citizens' Perception toward Introducing (VAT) is the dependent variable, and it is continuous in nature where the highest value represents the higher level of acceptance. On the other side, four predictor variables are considered in our study, which are; Perceived Usefulness of VAT, Perceived Ease of Use of VAT, Perceived Trustworthiness of VAT, and Perceived Risk of VAT. The regression model takes the following form:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p,$$

where.

X is the set of p predictor variables
α_j is the intercept,
β is the parameter for each predictor variable.

Empirical findings

To study the effect of the predictor variables on the dependent variable, namely, the Egyptian citizens' Perception, multiple linear regression analysis is performed. The results for the regression analysis are shown in Table 4.

All variables have a p-value < 0.05 (Perceived Usefulness of (VAT): 0.000, Ease of Use: 0.001, Perceived Trust: 0.000, and Perceived Risk: 0.002), suggesting that each variable has a statistically significant relationship with citizens' attitude. It should be noted that although the statistical analysis indicated that citizens had a positive attitude toward (VAT), there is still a need for more empirical studies to examine the effect of age, demographics, economic status, local people's accent, and personality traits of citizens; on the full acceptance and

Table 3 Multiple linear regression

Coefficients

Model	Unstandardized coefficients		Standardized coefficients	t	Sig	Collinearity statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	7.808E-17	0.033		0.000	1.000		
Usefulness of VAT	0.316	0.060	0.316	5.279	0.000	0.300	3.336
Ease of Use of VAT	0.189	0.059	0.189	3.220	0.001	0.313	3.198
Trustworthiness of VAT	0.284	0.057	0.284	4.996	0.000	0.332	3.010
Perceived risk of VAT	− 0.105	0.034	− 0.105	− 3.096	0.002	0.938	1.066

Dependent Variable: Citizens' Perception

Table 4 ANOVA

Model	Sum of squares	Df	Mean square	F	Sig	
1	Regression	229.540	4	57.385	134.672	0.000
	Residual	167.460	393	0.426		
	Total	397.000	397			

usage of the (VAT) in public services. The utilization of (VAT) is advantageous, and citizens generally support the adoption of the technology; nonetheless, it can be argued that Egyptians may have reservations, particularly during the initial phases of implementation, regarding system's accuracy and adequacy. Their hesitance to utilize the system may escalate. In public service delivery, it is advisable to gradually implement the automated system alongside the traditional approach. This mechanism allows citizens to be gradually introduced to automation while ensuring the availability of alternatives.

The regression findings showing the positive impacts of usefulness, ease of use, and trustiness, and the negative impact of perceived risk, were reflected in the qualitative findings. Most of the interviewees highlighted that Egyptian citizens are still wary of new technologies, with most needing transition periods where old and digital services coexist. This adds to the need to reduce perceived risk and incrementally build trust, as seen in quantitative findings as well. In addition, professionals pointed out that young adults would experiment with voice technologies but older segments less so—a subtlety that underlines the statistical proof of age-divergent acceptance.

Reasons for the above argument could be relevance to system's trustworthiness. Fully trusting a digitized system would effectively work only if the citizen were already familiar with the (VAT) usage. Awareness can initiate both trust and distrust based on past experience. Using (VAT) in public service delivery is Egypt is new to citizens. There is no recorded relevant bad experience regarding digitization of services in Egypt based on trust issues. On the contrary, Egyptian citizens have always trusted the official government outputs pertaining to personal credentials such as birth and marriage certificates, driving licenses, etc. However, it is always advisable, as indicated earlier, to use a parallel system along with the (VAT) in place until Egyptian citizens are familiar with the new technology.

There are several reports in the literature that support the above argument. A report published by PWC [45], PWC [46] regarding the use of (VAT) indicated that citizens' limited knowledge of the full breadth of VAT capabilities, their hesitation due to probable system complexity and its repercussions as well as the lack of trust, which will be discussed later in the study are the main reasons that VAT introduction activities beyond basics are rarely used.

Another element that could be added to the above, that is not exclusive to the Egyptian culture, is the resistance to change especially among elderly. According to Malodia et al. [35], the literature highlights that peoples' decisions to avoid or postpone the usage of a particular product or service are often influenced by factors that are different from the factors that initially influenced their adoption behavior. Scholars argue that understanding the underlying factors of avoidance and postponement, collectively termed consumer resistance, is as important as understanding the factors influencing adoption.

Resistance to change can be referred partially to (VAT) system's ease of use. Ease of use is very subjective. Something easy for one citizen to do may not necessarily be easy for another. The investigated sample represents those who are technology familiar. When the service is in place by the government, it should take into consideration the untrained and unexperienced users. For example, the designed (VAT) could vocally aid untrained citizens by performing the required actions automatically, but provide an interface for experienced users to select and use acceptable alternative actions. Adverse user experiences may impact the acceptance and utilization of a technology. The (VAT) must be structured to accommodate varying levels of user competence and experience.

Having said that, one could argue that people tend to be risk takers if the targeted element is of a small monetary value. This is somehow true, yet within the Egyptian context, the contrary could stand out especially in some social classes of the community. People would accept risk for moderate to large monetary values if they are assured that it is hassle free or to avoid other probable losses [10]. Convenience is a primary factor to consider in the Egyptian culture.

As indicated in Table 4, the P-value of ANOVA is $0.000 < 0.05$, which approved of the significance of the model.

Model diagnostics check

To make sure the results from regression analysis are reliable, normality and homoscedasticity assumptions must be fulfilled; while multi-collinearity and autocorrelation must be avoided. The normality assumption states that

Table 5 Model diagnostics

Homoscedasticity	
Chi2(1)	0.64
Prob > Chi2	0.71
Autocorrelation	
Durbin–Watson d-statistic	1.96
Normality	
Kolmogorov–Smirnov	0.122
Sig	0.317

the residuals of the model must be normally distributed with a mean of zero. The normality was tested through Kolmogorov–Smirnov [7]. The homoscedasticity states that the residuals must be approximately equal for all predicted dependent variables. Homoscedasticity was done through Breusch–Pagan test [32]. Multi-collinearity refers to the correlation among the independent variables which must be avoided [61]. Autocorrelation refers to the situation where the residual errors from a regression model are correlated with one another. This violates the assumption of independence in ordinary least squares (OLS) regression, potentially leading to biased estimates and inefficient statistical inference. In our study, we tested it through Durbin–Watson test [65].

In Table 5, the Breusch–Pagan test has a p-value of 0.71 (> 0.05), indicating that one cannot reject the null hypothesis and conclude that homoscedasticity is achieved. Autocorrelation was tested using the Durbin–Watson statistic, which ranges from 0 to 4. With a value around 2 in our model, no autocorrelation was detected in the data. Furthermore, the P-value of 0.317, which is higher than 0.05, indicates that normality has been attained [21].

The variance inflation factor (VIF) for each independent variable in the regression model is used to verify that multi-collinearity is avoided between the independent variables. In Table 3, VIF is lower than 5. VIF < 5 is generally considered acceptable, indicating no multi-collinearity between variables.

Machine learning predictions

The main aim of this intervention was to reach the best model to predict Egyptian citizens' Perception toward Introducing VAT to public service delivery. Accordingly, a multiple regression model was run to discover the factors that affect the dependent variable (citizens' perception) as seen in the previous section; then, an ML model was used.

In order to link one or more predictor variables with the outcomes, (ML) models employ computer algorithms to forecast the key variable, which is the perception of Egyptian citizens regarding the introduction of (VAT) to public service delivery. In the execution of (ML) models, demographic factors (such as gender, age, occupation, and education) were used alongside the primary four independent variables in the study as potential features for predicting citizens' perceptions. We estimate the models by seeking the optimal fit either deterministically or stochastically. The search procedure varied based on the algorithm employed.

The (ML) model classified data into two parts: train and test. The training data represent the examples used during the learning process to be able to fit the weights of each predictor. The testing data are independent of the training dataset, yet adhere to the same probability distribution as the training dataset. Ultimately, we can assess the model's efficacy in predicting the outcome variable. In this study, the training data constitute 80%, whereas the testing data comprise 20%.

Machine learning implementation

In this research study, supervised ML algorithms were applied. These predicted the targeted outcome (Egyptian citizens' perception toward introducing VAT) based on various features. The used ML models aimed to estimate the degree of perception among citizens by predicting a continuous outcome, influenced by multiple input features. Selecting the most appropriate (ML) method can be complex due to the variety of algorithms available and the influence of different data characteristics and problem-specific factors. To address this challenge, widely-used (ML) algorithms using Python were used, including Ridge Regression, Gradient Boosting Machine, Random Forest, Stochastic Gradient Descent (SGD), Support Vector Machine (SVM), Decision Tree, k-Nearest Neighbors, XGBoost, CatBoost, and LightGBM.

As shown in Table 6, ten (ML) approaches were utilized, and feature scaling through standardization was

Table 6 Parameters used in machine learning algorithms

Machine learning algorithms	Parameters
Ridge regression	Standard parameters
Gradient boosting Machine	Number of estimators = 100
Random forest	Number of estimators = 100
Stochastic gradient Descent (SDG)	Max number of iterations = 1000 Tol = 0.001
Support vector machine	Kernel is linear
Decision tree	Standard parameters
k-Nearest neighbors	Standard parameters
XGBoost	Number of estimators = 100
CatBoost	Number of estimators = 100
LightGBM	Number of estimators = 100

applied to ensure consistent feature scaling across models. The model performance is evaluated using Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root-Mean-Squared Error (RMSE) to obtain a comprehensive view of prediction accuracy. These metrics allowed to assess each model's predictive strength and select the most accurate method for continuous perception estimation.

Machine learning results

Several error metrics, such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root-Mean-Squared Error (RMSE), were used to assess how well the ML models perform. These matrices offered information about how well the models predict the desired results. While MAPE provided a percentage-based view of prediction accuracy, which was helpful for comprehending relative error. RMSE provided a more interpretable scale for quantifying the average amount of mistake. When combined, these measures provided a thorough evaluation of model performance and made it easier to compare models in order to determine the most correct strategy.

As shown in Table 7, the performance of various (ML) models is compared indicating that SGD and Ridge Regression are the top-performing models, achieving the highest level of accuracy of 71.92% and 70.94%, respectively, with relatively low error metrics (MSE, RMSE, and MAE). These models demonstrate strong predictive power and efficiency, making them highly suitable. Support Vector Machine, k-Nearest Neighbors, and Gradient Boosting also show good performance, with accuracy percentages above 67%, suggesting that ensemble methods are generally effective. In contrast, Random Forest, XGBoost, CatBoost, and LightGBM exhibit moderate performance, with accuracy percentages ranging from 64 to 66%, signifying diminished efficacy although remaining dependable. Decision Tree significantly underperformed, with low accuracy level of 49.33%, and had the highest error metrics, suggesting that it may not be well-suited for this dataset without further optimization. Overall, ensemble methods, particularly SGD and Ridge Regression, provided the most accurate predictions, while simpler models offered a trade-off between interpretability and accuracy.

Table 7 Comparison between machine learning algorithms' performance

Models	MSE	RMSE	MAE	Accuracy level
Ridge regression	0.358125	0.598435	0.42134	70.94%
Gradient boosting	0.400894	0.633162	0.455648	67.46%
Random forest	0.444423	0.666651	0.456421	63.93%
SGD	0.345969	0.588191	0.418641	71.92%
Support vector machine	0.388439	0.623249	0.43123	68.48%
Decision tree	0.624383	0.790179	0.523802	49.33%
k-nearest neighbors	0.399485	0.632048	0.482591	67.58%
XGBoost	0.424169	0.651282	0.455674	65.58%
CatBoost	0.428009	0.654224	0.45291	65.26%
LightGBM	0.421754	0.649426	0.459824	65.77%

(ML) deployment provides greater explanatory capability compared to classical regression. Although the majority of TAM-based adoption research is theoretically based on structural models (e.g., [15, 33]), in this study, Ridge Regression and SGD algorithms were shown to be capable of predictive accuracy higher than 70%, surpassing backdated models. This methodological extension enhances existing e-government acceptance studies, which seldom utilize predictive analytics to this extent. The low performance of the Decision Tree model (49.3%) is also indicative that all ML methods are not universally suitable to the task of forecasting citizen adoption, consistent with calls in the literature for more context-dependent testing of AI-based models [24].

Figure 3 compares the predicted values from the Stochastic Gradient Descent (SGD) and Ridge Regression models against the actual target values. These two models were selected based on their lower Mean Squared Error (MSE) scores, indicating a stronger predictive performance in this context. In the graph, the black line represents the actual values, providing a baseline for assessing prediction accuracy. The dashed lines show the predicted values for each model. Observing how closely these lines follow the actual values allows us to evaluate each model's effectiveness. Ridge Regression and SGD exhibit varying levels of alignment, highlighting the consistency and possible strengths of each model in capturing the underlying patterns of the data.

Compared with past e-government research, where only usefulness and usability were taken into consideration [13, 56], the current study demonstrates how trust and perceived risk are equally significant in taking the citizens' willingness to adopt VAT in Egypt into consideration. This result is corroborated by Jarvenpaa et al. [29], who believed that trust is relative to culture, and Hofstede et al. [26], who demonstrated that high-uncertainty avoidance societies like Egypt will be resistant to first disruptive technologies. Based on both quantitative and qualitative data, this research adds to a more comprehensive VAT adoption perspective. Further, the incorporation of ML predictive models puts this study at the intersection of (AI) and public administration and extends the TAM framework with the provision of a new methodological avenue for future research in developing-country settings.

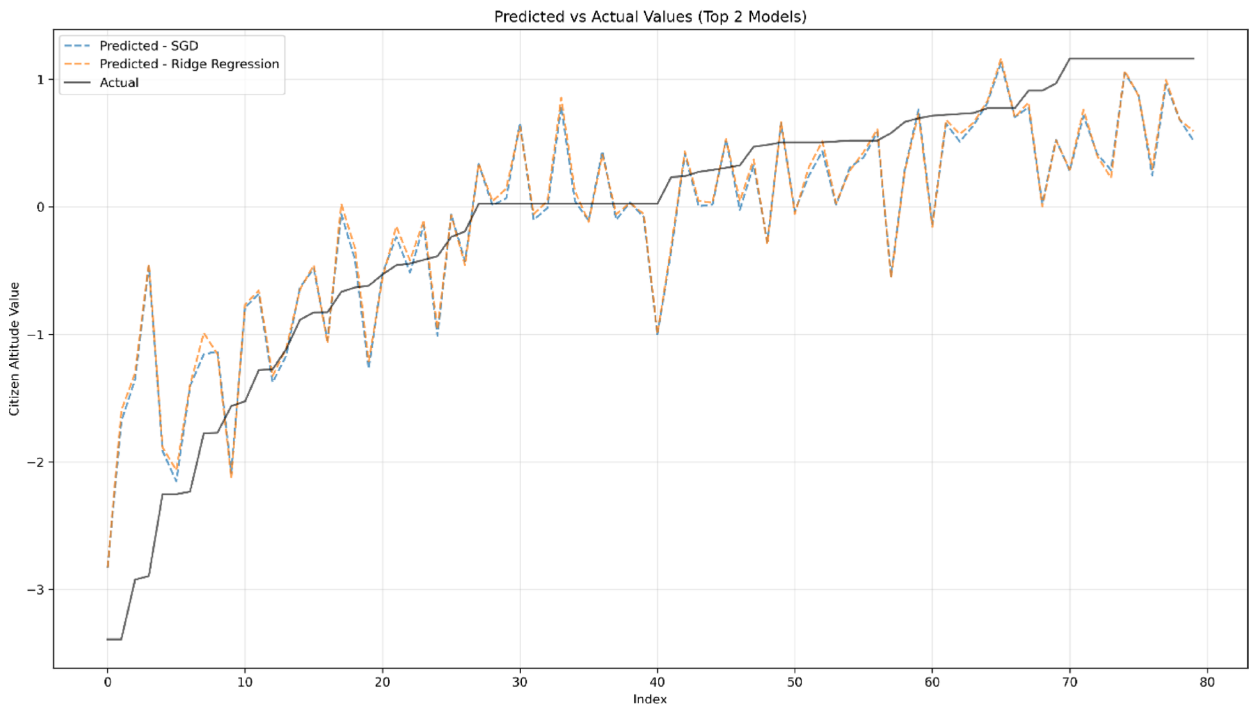

Fig. 3 Comparison of predicted vs. actual values for top regression models: SGD and ridge regression

Conclusions and implications

This research offers a novel contribution to understanding the acceptability of Voice Assistant Technology (VAT) in public service delivery. By extending the Technology Acceptance Model (TAM) with trust and perceived risk, and by employing machine learning (ML) predictive models, the study advances beyond descriptive analysis to integrate behavioral theory with computational approaches. This dual framework provides a more holistic and accurate understanding of technology adoption in Egyptian public administration within a developing-country context.

The findings demonstrate that perceived usefulness, ease of use, and trust significantly encourage VAT acceptance, while perceived risk acts as a barrier. Importantly, the ML results not only corroborate regression findings but also illustrate the promise of predictive analytics in forecasting adoption trends—an innovation rarely applied in public administration scholarship. This highlights the originality of the study in linking classic theoretical models with contemporary data-driven practices.

Theoretical contribution

Theoretically, this study enriches technology adoption literature by formally integrating trust and risk constructs into TAM, a step particularly valuable in high-uncertainty contexts such as Egypt. Moreover, applying ML predictive modeling represents a methodological advancement, showing how computational techniques can complement traditional adoption frameworks and provide predictive power for social science research.

Practical contribution

For policymakers and technology developers, the results provide actionable guidance. Trust-enhancing measures—such as transparent communication, robust data protection, and citizen education—should be prioritized to address risk perceptions. A phased roll-out of VAT, combining digital and traditional services, can ease adoption among older or less digitally experienced groups. At the same time, engaging youth as early adopters can accelerate cultural acceptance. Finally, public administrators can leverage ML tools to optimize resource allocation, design targeted awareness campaigns, and implement inclusive interventions that support sustainable digital transformation.

Limitations

Like any empirical research, this study operates within certain boundaries. The use of a convenience sample allowed for practical data collection but may not fully represent the broader Egyptian population. Similarly, self-reported data capture perceptions effectively but may be influenced by personal bias. The cross-sectional design offers a useful snapshot of citizen attitudes but does not capture how these perceptions might evolve over time. Finally, the study's focus on Egypt ensures contextual depth, though it naturally limits immediate generalization to other developing countries. These boundaries should be viewed as opportunities for future research rather than weaknesses of the current study.

Further research

Building on these findings, future research could employ longitudinal designs to track shifts in VAT perceptions and adoption behavior over time. Comparative studies across different cultural and regional contexts would shed light on how adoption dynamics vary internationally. Expanding the model to include additional mediators and moderators—such as digital literacy, cultural orientations, or infrastructural readiness—could provide richer explanatory insights. Finally, experimental or field-based research on actual VAT usage in government service centers could bridge the gap between adoption intention and practical implementation.

Appendix

The survey questionnaire

We are conducting a research study to evaluate Egyptian citizens' perception toward the viability of using (VAT) as a means of improving public service delivery. Kindly fill in the following questionnaire as honest as possible.

Theme	Statements	(5) Strongly Agree	(4) Agree	(3) Neutral	(2) Disagree	(1) Strongly Disagree
Perceived Usefulness of VAT	1. Using Voice Assistant Technology would save my time in governmental offices and authorities					
	2. Voice Assistant Technology provides hand-free operations around public service offices					
	3. Using Voice Assistant Technology increases officials' productivity in public service offices					
	4. Service provided via Voice Assistants can be cost effective for the Citizen and the State					
	5. Voice Assistant Technology can provide 24/7 support for public seeking service delivery					
	6. Voice Assistant Technology can be utilized frequently without difficulty					
	7. Voice Assistant Technology can be useful for literate and illiterate citizens					
	8. Voice Assistants can be accessed via a machine in the governmental offices or via a mobile application					
Perceived Ease of Use of VAT	9. Voice Assistants could be user friendly and can accommodate citizen preferences and requests					
	10. Voice Assistants can be designed for technology literate and illiterate citizens					
	11. Voice Assistant Technology would not easily allow citizens to select the wrong choices or cause an error					
	12. Voice Assistants would allow easy recovery when citizens make a wrong choice					
	13. Voice Assistants would use a language that can be easily understood by citizens from different governorates					

Perceived Trust-worthiness	14. Using Voice Assistant Technology provides instant access to information and it is better than dealing with state officials
	15. Voice Assistants can be used in government services without any degree of uncertainty of intention. (No Hidden Agenda)
	16. Government service provided via Voice Assistants would be transparent, reliable, and direct
	17. Voice assistants would offer services equivalent to those provided by traditional methods
Perceived Risk	18. Voice Assistants may dysfunction while using the service leading to waste of time
	19. Voice Assistants may incur expenses without delivering the required output
	20. Voice Assistants may be complicated to use and would lead to queuing of citizens
	21. Voice Assistants can might lead to leakage of personal information
	22. Voice Assistants can might lead to leakage of financial information
Citizens' Attitude (Acceptance and Utilization of VAT)	23. I would use Voice Assistants to ease my daily tasks
	24. I could save much time using Voice Assistant Technology
	25. I would feel comfortable sharing information through my voice assistants
	26. I would be enthusiastic if Voice Assistants is introduced to all public offices
	27. I could totally rely on my Voice Assistant in my daily life activities

Parameters of service usefulness

- Convenience
- The levels of engagement for features across different segments of users.
- Frequency of usage
- The location, device, and time user engagement.
- Time-to-value.
- Time spent using the product.
- Cost-effectiveness

Parameters of service ease of use

- Usability
- Error proof
- Credibility

Parameters of service ease of use

- Accessibility
- Credibility
- Certainty of intention
- Dependability
- Confirmability

Parameters of risk

- Functionality
- Complexity
- Cost
- Honesty and credibility

Author contributions
K.S., I.L., and Y.T. have scrutinized the literature and formulated the research gap. Additionally, they wrote a literature review. H.T., Y.T., and K.S. formulated the methodical framework of this study to achieve the desired objectives. They selected the sample size from the available population and designed, together with I.L., the data collection instrument and suggested the method of data analysis. I.L., H.T., and Y.T. have presented the discussion of results. The discussion of the different collected data is presented in the results. Y.T., H.T., and K.S. contributed to this research by collaborating with I.L. in the design of the data collection instruments. All authors have read and approved the manuscript.

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Data availability
Authors confirm that all the data and materials are available

Declarations

Ethics approval and consent to participate
This research was performed in adherence to national and institutional research ethics guidelines on human subjects. The study's protocol was ratified by a local ethics review board and concluded that no official approval was needed because of its low-risk nature but asked for an end copy of the published article. All subjects were informed of the study's aim, method, and rights before taking part. Electronic informed consent was asked prior to completing the questionnaire and verbal prior to expert interviews. Participation was wholly voluntary, and participants were allowed to withdraw at any time without penalty. Confidentiality was maintained by not asking any identifiers and anonymizing and storing all responses securely. In the opinion of authors, the study follows the ethical principles of the Declaration of Helsinki.

Consent for publication
Consent for participant is not applicable.

Competing interests
The authors declare no competing interests.

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