Assessing the Acceptance for Implementing Artificial Intelligence Technologies in the Governmental Sector

An Empirical Study

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ABSTRACT

Artificial Intelligence (AI) has been recently implemented in various advanced government applications, including security, transportation, and healthcare. The wide variety of AI applications raised the issue of adoption difficulties in governmental usage, which is what this study investigates. More specifically, the present study examines the relationship between personnel perceptions and organizational, technological, and environmental factors that affect the AI acceptance and adoption in the governmental sector. To this end, a conceptual framework integrating the Technology Acceptance Model (TAM) with the Technology Organization Environment (TOE) is proposed and evaluated, where a survey for collecting relevant data from 179 employees working in four Palestinian ministries was utilized. The Partial Least Squares-Structural Equation Modeling (PLS-SEM) analysis of data using Smart PSL 4.1.0.8 revealed a significant association between TAM constructs and AI acceptance and adoption. Specifically, the relationships between the TOE variables and TAM's Perceived Usefulness (PU) or Perceived Ease Of Use (PEOU) were significant, except for the legal framework and organizational readiness relationship with PEOU. Besides the analytical investigation, this paper contributes practical insights into AI implementation in the government sector emerging from personnel perspectives. Theoretically, the study analyzes the validity of the conceptual model and thoroughly investigates its constructs and factors, hence suggesting that the

governmental ministries focus on the linkage between institutional factors and individual AI perceptions for the latter'seffective acceptance and adoption.

Keywords-AI; technology adoption; governmetnal sector; TOE framework, TAM

I. INTRODUCTION

The world is experiencing a fast development in the field of technology in the present Industry 4.0 revolution era, either in the form of developing new technologies or improving the already existing ones [1, 2]. To cope with such a development, institutions and governments must act urgently to transition from antiquated systems to more sophisticated digital ones. This transition is inevitable because there is sufficient evidence that using remote technologies to conduct transactions without the need of human intervention would result in significant benefits [3]. The AI term first arose in the early 20th century [4, 5]. Authors in [6] mention that AI was first studied in the 1940s to address the question of how machines could replace human beings in making decisions. Utilizing new technologies, like AI, governance, public services, and social values can be improved, while citizen satisfaction can be increased. These factors will make governments interested in achieving effectiveness in their procedures and services. Applying AI in governmental fields creates new careers. Also, the governmental resources are exploited for the necessary efficiency and effectiveness in conducting transactions to be achieved, particularly for governments that struggle with resource scarcity [7-9]. According to [10], the public value theory is primarily concerned with the ethical issues surrounding good governance, the government's reputation, and the analysis of decision-makers in the government. Accuracy, justice, equality, and transparency are just a few of the values attained by AI technologies.

Numerous studies have examined the use of particular technologies in a range of industries, where the Theory of Reasoned Actions (TRA) from which numerous models have been developed, is one of the theories that have been extensively used. In this study, the TAM is adopted [11, 12]. The two primary factors that the TAM measures, are PU and PEOU [12]. More specifically, PU assesses whether the user or citizen feels that applying the new systems would improve their life or career, while the PEOU determines to what extent the user feels that they need education and training to begin using new technology effectively [13]. TAM is a standard model deployed to improve decision-making when switching to a new digital system by assessing the new system's utility and usability [14]. By characterizing the effectiveness and usability of AI, TAM provides a logical framework to assess citizen acceptance of its use in public services. However, TAM also has shortcomings. One of its limitations is that it could only take into account user perceptions without defining the external variables in the model; to address this, it was required to expand some of the existing factors or access additional factors that went beyond TAM's bounds [15]. According to [16], TOE is an analytical framework for research that looks at various institutional aspects in an effort to match theory with practice. It primarily looks for ways in which the institution itself can accept new technology from three perspectives, which are: technological, organizational, and external environmental factors. More specifically, the technical level at which the institution is currently operating, its strengths and weaknesses, and its technical efficiency are all considered technological factors. Organizational factors are related to the institution's administrative system, managers, employees, and the procedural administrative aspects involved. The environmental factors are related to external influences that impact the institution and are influenced by its policies regarding new technology adoption [10, 17].

Earlier researches have rarely looked at the acceptance and adoption of AI technologies in governments using measures of personnel attitudes and their relations with other managerial and institutional factors. Accordingly, the proposed work takes these factors into account by focusing in the Palestinian government and passing the study outcomes to the governmental decision-makers to be aware of the challenges that may impede AI successful adoption [18]. The challenges can be prioritized during the planning phase and flaws can be highlighted by measuring the variables that are helpful in determining the appropriate course of action for early governmental administrative decisions prior to the actual AI adoption. Authors in [19] give comprehensive information about applying AI in an ambient intelligence system for healthcare, which shows in what way AI adaptation is important in government services. Table I summarizes the model hypotheses.

II. METHODOLOGY

A. Research Design

The TOE-TAM is a theoretical explanatory research model that clarifies the factors influencing new technology adoption [37], and as an explanatory research model, it investigates the relationships between many components explaining why certain events occur. The information acquired can help make well-informed judgments that can aid in creating interventions or enhancing existing procedures [38]. Understanding why some technologies are successfully adopted while others may not necessarily do so in various contexts is helpful. To a certain degree, individual perceptions in technology adoption are influenced by technological, organizational, and environmental factors as well. When taken as a whole, these elements add an even more in depth explanation of how technology adoption is accepted, assisting practitioners and researchers in comprehending why people embrace or reject various forms of technology [39]. The fact that quantitative data can be gathered and examined using statistic, quantitative research can be very beneficial. This makes it possible to determine correlations between the TOE-TAM variables and their relationship. It would be feasible to examine a number of factors with quantitative research, such as human perceptions of new technology, TOE factors, and technological understanding [40].

TABLE I. MODEL HYPOTHESES

Hypothesis	Supporting Researches	Explanation
H1: PU of AI technologies in the Palestinian government is significantly impacted by relative advantage.	[16, 20-24]	Relative advantage, i.e., the perception that AI offers more benefits than previous technologies, positively impacts the perceived usefulness (PU) of AI.
H2: PEOU of AI technologies in the Palestinian government is significantly impacted by compatibility.	[23, 25-27]	Compatibility, or how well AI integrates with existing systems and workflows, positively impacts the PEOU of AI.
H3: The PU of AI technologies in the Palestinian government is significantly impacted by complexity.	[20, 22]	Complexity, or the difficulty in learning and using AI, negatively impacts the PU of AI.
H4: The PEOU of AI technology in the Palestinian government is significantly impacted by observability.	[25, 28, 29]	Observability, or the visibility of AI's benefits, positively impacts the PEOU of AI.
H5: The PU of AI technology in the Palestinian government is significantly impacted by top management support.	[22, 28, 30]	Top management support for AI adoption positively impacts the PU of AI.
H6: The PU of AI technology in the Palestinian government is significantly impacted by managerial capability.	[8, 31, 32]	Managerial capability in understanding and implementing AI positively impacts the PU of AI.
H7: The PEOU of AI technology in the Palestinian government is significantly impacted by organizational readiness.	[23, 33]	Organizational readiness, in terms of resources and change-friendly environment, positively impacts the PEOU of AI.
H8: The PEOU of AI technology in the Palestinian government is significantly impacted by legal framework.	[32]	A clear legal framework governing AI usage positively impacts the PEOU of AI.
H9: The PEOU of AI technology in the Palestinian governments is not significantly impacted by competitive pressure.	[31, 34]	Contrary to expectations, competitive pressure does not significantly impact the PEOU of AI.
H10: The PU of AI technology in the Palestinian governments is significantly impacted by PEOU of AI technologies.	[35]	PEOU positively impacts PU, as ease of use allows users to focus on AI's benefits rather than its complexity.
H11: The PEOU of AI technologies significantly affect the behavioral intention (BI) of the Palestinian government.	[13, 35]	PEOU positively impacts BI, as ease of use motivates users to adopt and use AI in their daily operations.
H12: The PU significantly affects the behavioral intention (BI) of AI technology in the Palestinian government.	[35, 36]	PU positively impacts BI, as perceived usefulness drives users to adopt and use AI technology.

Structural Equation Modeling (SEM) is a useful technique used across numerous fields [41]. Partial Least Squares SEM (PLS-SEM)) is particularly helpful when researchers wish to concentrate on prediction with the chance to comprehend and anticipate relationships [42]. By these statistical methods, model reliability and validity criteria, as well as other statistical measures utilized to evaluate the model and hypotheses can be examined by using Smart PLS 4.1.0.8 version.

B. Data Collection and Sample Size

The study population consists of the government employees who stand to be impacted by the AI system's adoption. Government representatives, legislators, IT specialists, and other stakeholders in decision-making and execution may fall under this category.

This research uses a purposive sample of respondents who are either in management positions or who are knowledgeable or experienced in the topic of study and are being suggested for using AI in their job. The respondents were from a variety of ministries; namely, the Ministry of Telecommunication, and other ministries that have a strong connection to AI operations, including the Ministries of Health, Interior, and Labor.

PLS-SEM has the ability to handle small sample sizes. Samples can be taken based on the model's relations, particularly when using the 10-times method [42], which takes under consideration the number of relations toward a construct. For the model, this means that the minimum sample size would be 60, since the largest number of relations is 6 indicators pointing to PEOU. Based on the analysis performed in [43], which establishes a relationship between the number of arrows at a construct, the R^2 value, and the significant level, the minimum sample size would be 75. Furthermore, according to [44], 160 was the minimal sample size for PLS-SEM in order to meet the requirements of particular statistical techniques. Therefore, a purposive sample of 179 respondents was used in this study, which satisfies the previously-mentioned criteria of sample size.

C. Study Instrument

The work on the questionnaire went through multiple phases. By analyzing earlier researches in TAM and TOE and how they addressed these constructs in their quantitative analysis, at the first step, all indicators having an impact on each construct in the model were defined. After that, the questions were written in an appropriate language, and then this questionnaire was shown as a pilot testing for two academics and three IT specialists. An online link was made to complete a self-administered questionnaire consisting of questions for collecting the demographic information of respondents. A five-point Likert scale, 5: strongly agree; 4: agree; 3: neutral; 2: disagree and 1: strongly disagree, was adopted to obtain perceptions from respondents. More specifically, 6 questions were asked to measure relative advantage (REL1-REL6), 3 questions were asked for compatibility (COMP1-COMP3), 2 for complexity (COMPLEX1-COMPLEX2), 4 for observability (OBS1-OBS4), 3 for top management support (TMS1-TMS3), 4 for managerial capacity (MC1-MC4), 3 for organizational readiness (OR1-OR3), 3 for legal framework (LF1-LF3), and 2 for competitive pressure (CP1-CP2). Also, there were 2 questions on PU (PU1-PU2), 2 on PEOU (PEOU1-PEOU2), and 2 on BI (BI1-BI2).

Owing to an inadequate quantity of surveys, paper-based questionnaires were created and disseminated among the staff members to guarantee the attainment of a suitable sample size. Social media ςερε used to disseminate the online survey, which received 94 valid responses as of the analysis's start date. Regarding the paper responses, 85 valid responses could be obtained.

III. DATA ANALYSIS AND RESULTS

A. *Modification on the Model*

Figure 1 presents the initial model which includes nine constructs from the TOE framework.

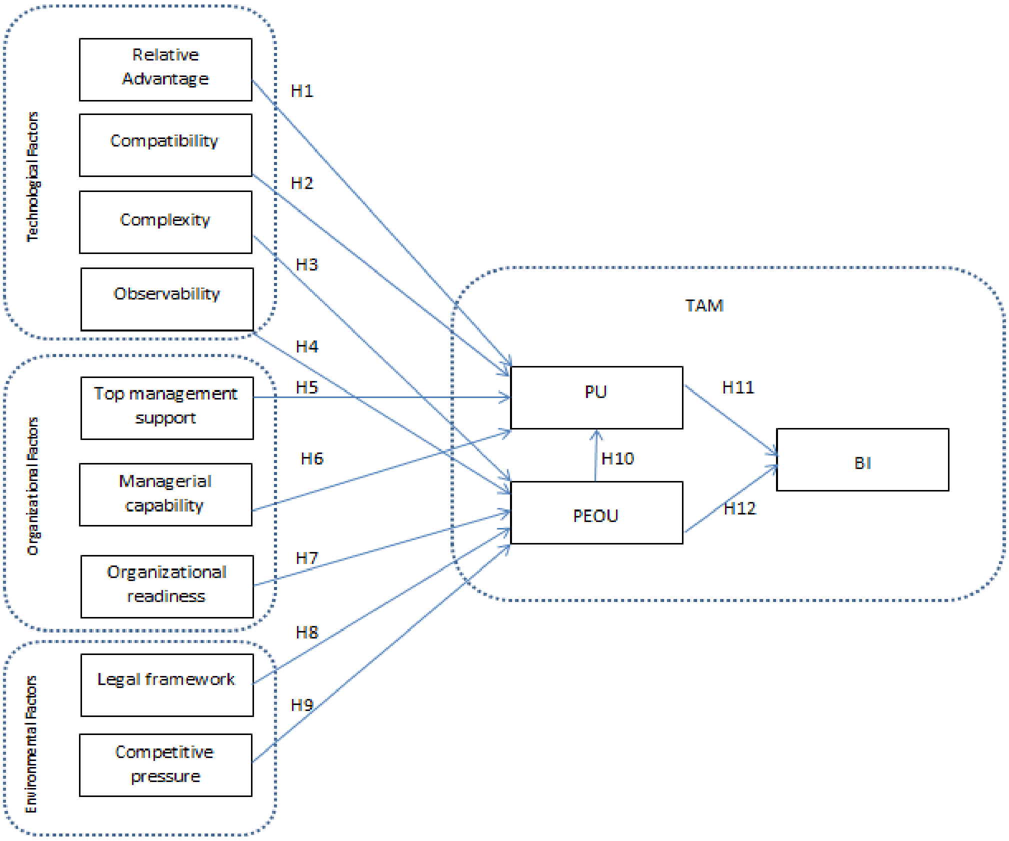

Fig. 1. The initial TAM.

However, upon conducting the analysis, it became evident that there were issues with the model's validity and reliability in particular. As a result, the "Complexity" construct was removed in order to improve the model's criteria. This decision can be justified in several ways. When checking reliability and validity, it was found that the Cronbach alpha value for Complexity construct was 0.485, which is less than the threshold of 0.7, found in [43]. Also Heterotrait-Monotrait ratio (HTMT) values for this construct and those of other constructs exceeded 1.0, which is an indication for invalidity issues [41]. The effect (f^2) value for "Complexity" was found to be 0.005, less than 0.15 and this means [43], that the R^2 for the following construct, which is PU in our case, is not affected by this construct. Moreover, when looking to the outer loading values for the two indicators of these constructs, which are COMPLX1 and COMPLX2, they were found to be 0.9 and 0.673, respectively, with the latter being less than the threshold value of 0.7 [45]. Previous studies, like [46], allow deleting up to 20% of a model's elements in order to fix reliability and validity problems. In the proposed model, the indicator COMPLX2 was firstly deleted. After this deletion, the outer loading value of COMPLX1 became 0.615, which is less than threshold (0.7). So, it was also deleted.

B. *Descriptive Analysis for Respondents Demographics*

Table II summarizes the descriptive statistics of the respondents' demographic information. About 75% of the respondents were male, between 20-39 years old, and having engineering or management positions in their institutions. Less than 15% of them had a non-university education.

TABLE II. INFORMATION OF RESPONDENTS.

Category	Sub-Category	Frequency	Percent
Gender	Female	50	28%
	Male	129	72%
Age	20-29	67	37%
	30-39	69	39%
	40-49	25	14%
	50-59	18	10%
Qualification	Diploma	24	13%
	Bachelor	97	54%
	Graduate Studies	58	32%
Job Position	Manager/ not engineer	28	16%
	Manager/ engineer	50	28%
	Managerial position	56	31%
	Others	45	25%

C. The Measurement Model

In PLS-SEM, the measurement model evaluates the connections between constructs, or latent variables, and their indicators. It contributes to the accuracy with which the measurement indicators represent the constructs that they are supposed to represent [41]. The consistency and stability of the measurement indicators, such as outer loadings, Cronbach's alpha, and Composite Reliability (CR), are the main concerns of reliability testing. Convergent and discriminant validity tests are also used as validation procedures to ensure that the measurement indicators are, in fact, assessing the intended construct. Model fit checks assess how well the data fit the PLS-SEM model [47]. Figure 2 depicts the PLS-SEM's measurement model generated by the Smart PLS 4.1.0.8. The correlations between the observed variables and their related latent variables are referred to as outer loadings. The loadings have a significant influence on the PLS-SEM measurement model determination.

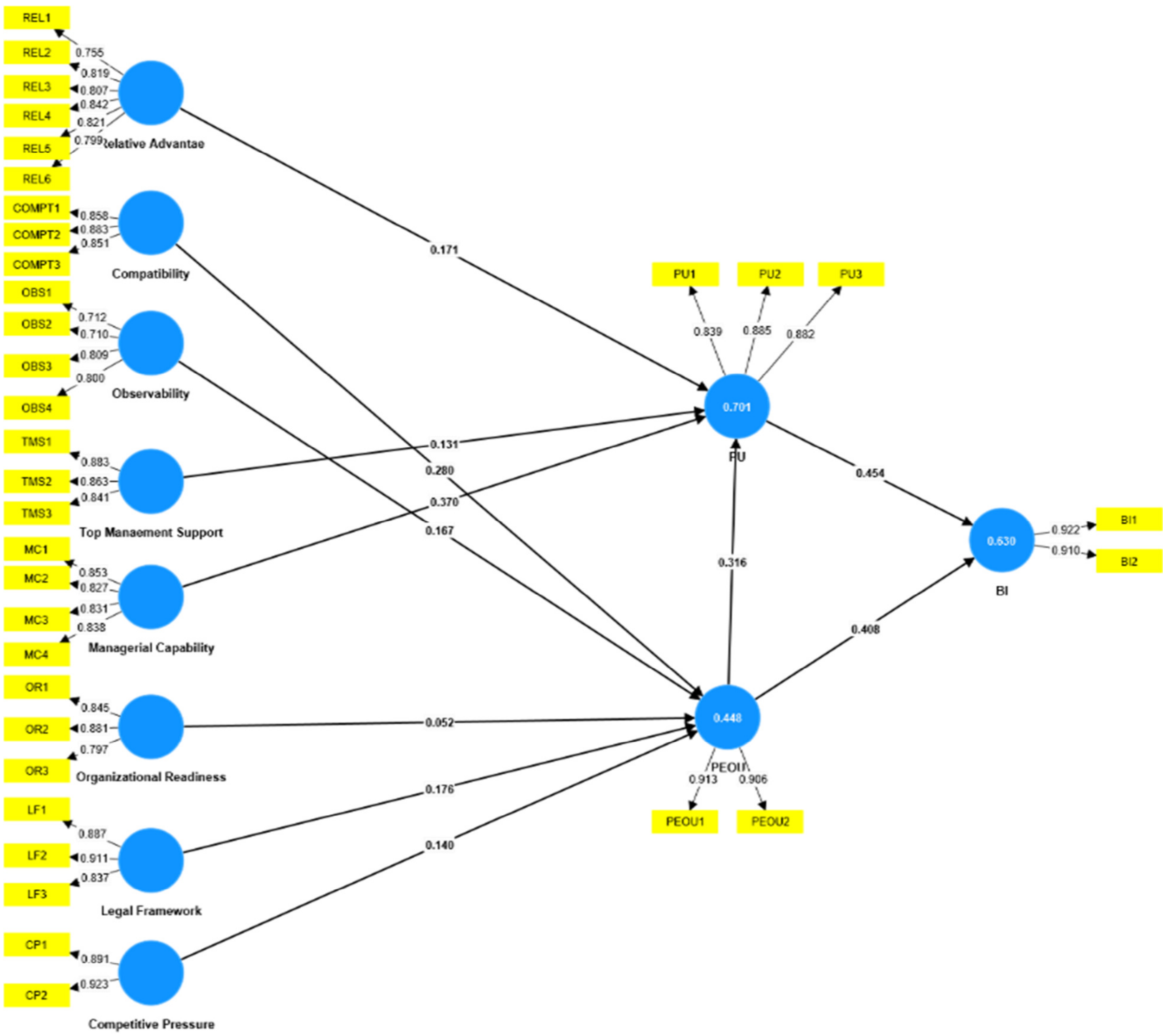

Fig. 2. The PLS-SEM measurement model.

The values of outer loadings vary from -1 to 1. The relationship between the dependent variable and its covert variable is stronger if the absolute value approaches 1. The outer loading should, in most cases, be more than 0.7, which indicates that more than half of the variance in the latent variable should be explained by the observable variable [43]. Table III shows all of the outer loadings that were determined and found to be greater than 0.7 in the research model.

Cronbach's alpha is one of the most often used metrics of reliability [47]. It demonstrates that the indicators are clear and well-defined and provides an indication of how consistently the construct holds up with its indicators. All model constructs have values over 0.7, and a value higher than 0.7 is considered acceptable [41]. The alpha values for the research model are depicted in Table III. All values are over the 0.7, and hence internal consistency is confirmed. CR is an additional internal consistency metric that is thought to be a more accurate measure and a tool to determine whether a particular construct is consistent and reliable, or not. Similarly to Cronbach alpha, a value greater than 0.7 is considered acceptable [43]. In contrast to Cronbach alpha, CR takes into account all indicator factor loadings. All CR values are over the 0.7 (Table III) thresholds, and thus reliability is confirmed. The third measure, known as Average Variance Extracted (AVE), is a crucial tool for examining both convergent validity and reliability in SEM. It can be used to measure reliability with a cutoff value of 0.5, indicating that the construct is well away from measurement errors [47]. The AVE is calculated by averaging the squared correlations for each indicator on the construct under study. Higher AVE values suggest higher convergent validity. If half or more of the variability on the indicators is attributable to the construct, then an AVE criterion of 0.50 and above can be often considered appropriate [43]. All AVE values are greater than 0.5 (Table III), and hence convergent validity is confirmed.

The indicator of discriminant validity that shows how each construct in the model is unique from the others is the HTMT ratio. It allows researchers to look at how one construct relates to other constructs and vice versa. Although research papers accept HTMT to be up to 1, the default acceptable value in Smart-PLS is 0.85 [43]. Table IV summarizes the HTMT values of the model. All values are below the threshold of 1.00, which the researchers used to determine the HTMT's recognized validity [48].

TABLE III. MEASUREMENT PROPERTIES

Construct	Cronbach's alpha	(CR)	AVE	Item	Outer Loadings
Relative Advantage	0.893	0.898	0.652	REL1	0.755
				REL2	0.819
				REL3	0.807
				REL4	0.842
				REL5	0.821
				REL6	0.799
Compatibility	0.83	0.831	0.839	COMPT1	0.858
				COMPT2	0.883
				COMPT3	0.851
Observability	0.755	0.763	0.576	OBS1	0.712
				OBS2	0.71
				OBS3	0.809
				OBS4	0.8
Top management support	0.829	0.841	0.744	TMS1	0.883
				TMS2	0.863
				TMS3	0.841
Managerial Capability	0.858	0.86	0.701	MC1	0.853
				MC2	0.827
				MC3	0.831
				MC4	0.838
Organizational Readiness	0.797	0.819	0.708	OR1	0.845
				OR2	0.881
				OR3	0.797
Legal Framework	0.854	0.869	0.773	LF1	0.887
				LF2	0.911
				LF3	0.837
Competitive Pressure	0.786	0.801	0.823	CP1	0.891
				CP2	0.923
PU	0.838	0.84	0.756	PU1	0.839
				PU2	0.885
				PU3	0.882
PEOU	0.792	0.793	0.828	PEOU1	0.913
				PEOU2	0.906
BI	0.809	0.811	0.746	BI1	0.922
				BI2	0.91

TABLE IV. HTMT VALUES

Construct	BI	Compatibility	Competitive Pressure	Legal Framework	Managerial Capability	Observability	Organizational Readiness	PEOU	PU	Relative Advantage
Compatibility	0.70									
Competitive Pressure	0.61	0.65								
Legal Framework	0.71	0.72	0.77							
Managerial Capability	0.73	0.79	0.81	0.84						
Observability	0.71	0.72	0.61	0.62	0.68					
Organizational Readiness	0.65	0.73	0.75	0.93	0.83	0.53				
PEOU	0.90	0.72	0.64	0.67	0.68	0.65	0.62			
PU	0.89	0.75	0.77	0.74	0.88	0.70	0.70	0.85		
Relative Advantage	0.74	0.95	0.65	0.65	0.70	0.67	0.67	0.69	0.769	
Top Management Support	0.69	0.82	0.74	0.83	0.87	0.76	0.84	0.66	0.816	0.74

When examining the constructs' correlations with one another, discriminant validity is considered proven if each construct has the highest correlation with the value on the same row in the Fornell-Larcker matrix. Table V summarizes the Fornell-Larcker values exhibiting that each diagonal value is the greatest in its column [48].

TABLE V. FORNELL-LARCKER VALUES

Construct	BI	Compatibility	Competitive Pressure	Legal Framework	Managerial Capability	Observability	Organizational Readiness	PEOU	PU	Relative Advantage	Top Management Support
BI	0.91										
Compatibility	0.57	0.86									
Competitive Pressure	0.49	0.53	0.90								
Legal Framework	0.60	0.61	0.62	0.87							
Managerial Capability	0.61	0.67	0.66	0.72	0.83						
Observability	0.49	0.51	0.42	0.43	0.49	0.78					
Organizational Readiness	0.53	0.59	0.59	0.77	0.70	0.36	0.84				
PEOU	0.72	0.59	0.51	0.56	0.56	0.48	0.51	0.91			
PU	0.73	0.62	0.63	0.63	0.75	0.51	0.58	0.69	0.86		
Relative Advantage	0.63	0.81	0.55	0.57	0.61	0.49	0.57	0.58	0.67	0.80	
Top Management Support	0.57	0.68	0.60	0.70	0.74	0.56	0.68	0.54	0.68	0.64	0.86

Common method Bias (CMB) in PLS-SEM refers to the phenomenon of measuring techniques used in evaluating causes and effects in a model. Indicators may share some variation, such as guidelines or the implicit social appeal of providing a specific response to a questionnaire question. To evaluate the presence of CMB, Variance Inflation Factors (VIF) values larger than 3.3 are used [49]. Productive relevance is determined utilizing the predictive sample reuse approach (Q2), which deploys cross-validated redundancy techniques to predict removed data points. When Q2 is greater than zero, it indicates predictive relevance [50]. Multi-collinearity can affect results and interpretation based on the PLS model in Smart PLS 4.1.0.8, resulting in unstable regression parameters and inflated standard errors. VIF values lower than the default value of 5 in Smart PLS 4.1.0.8, indicate no collinearity problems in the data [51]. The analysis revealed that all VIF values are below 5, and hence not multi-collinearity exists in the model.

TABLE VI. MODEL FIT INDICES

Index	Saturated model	Estimated model
SRMR	0.063	0.066
NFI	0.699	0.699

Model fit is defined as the model's reliability and ability to fit data and generalize results. The Standardized Root Mean Squared Residual (SRMR) index, which represents the mean absolute value of covariance residuals, is considered a good fit in Smart PLS 4.1.0.8. A large fit is defined by the Goodness-Of-Fit (GOF), which is greater than 0.36 [52]. A fit of less than 0.08 or less than 0.10 is regarded as acceptable [44]. Since the value in this case is 0.063, below the cutoff, the model fit is deemed acceptable. Also, Normal Fit Index (NFI) seems to be less than 0.9, which is the recommended lower value for this measure. Authors in [42] consider that thresholds for such a measure are problematic and need more exploration and so the model will be able to fit PLS-SEM properly [53]. Table VI shows the model fit indices.

D. Assessment of the Structural Model

The structural model is depicted in Figure 3, where the structures are represented by R^2 values and the connections by P and B values. The R^2 statistic, which indicates to what extent the independent variable is made up of dependent variables, is the initial measurement. It is a number between 0 and 1, and the closer it is to 1, the more variables are used to define it in this form. R^2 is a metric used to represent how variables relate to one another in a model and how much a given construct is expressed by the variables that make up that construct. All values of R^2 (Table VII) exceed the 0.2 criterion. The constructs of BI account for 63% of the construct. PEOU constitutes 44.8% of organizational readiness, observability, legal framework, and competitive pressure, and PU accounts for 70% of the variance.

TABLE VII. R-SQUARED VALUES

Dependent Variable	R-square	R-square adjusted
BI	0.630	0.626
PEOU	0.448	0.433
PU	0.701	0.695

E. Testing the Research Hypotheses

The analysis findings provide helpful correlations between several elements. With a P-value of 0.000, the management capability B-value of 0.370 indicates a significant influence on PU. This implies that a rise in managerial skills would result in a significant increase in PU. P-values and path coefficients are illustrated in the Table VIII.

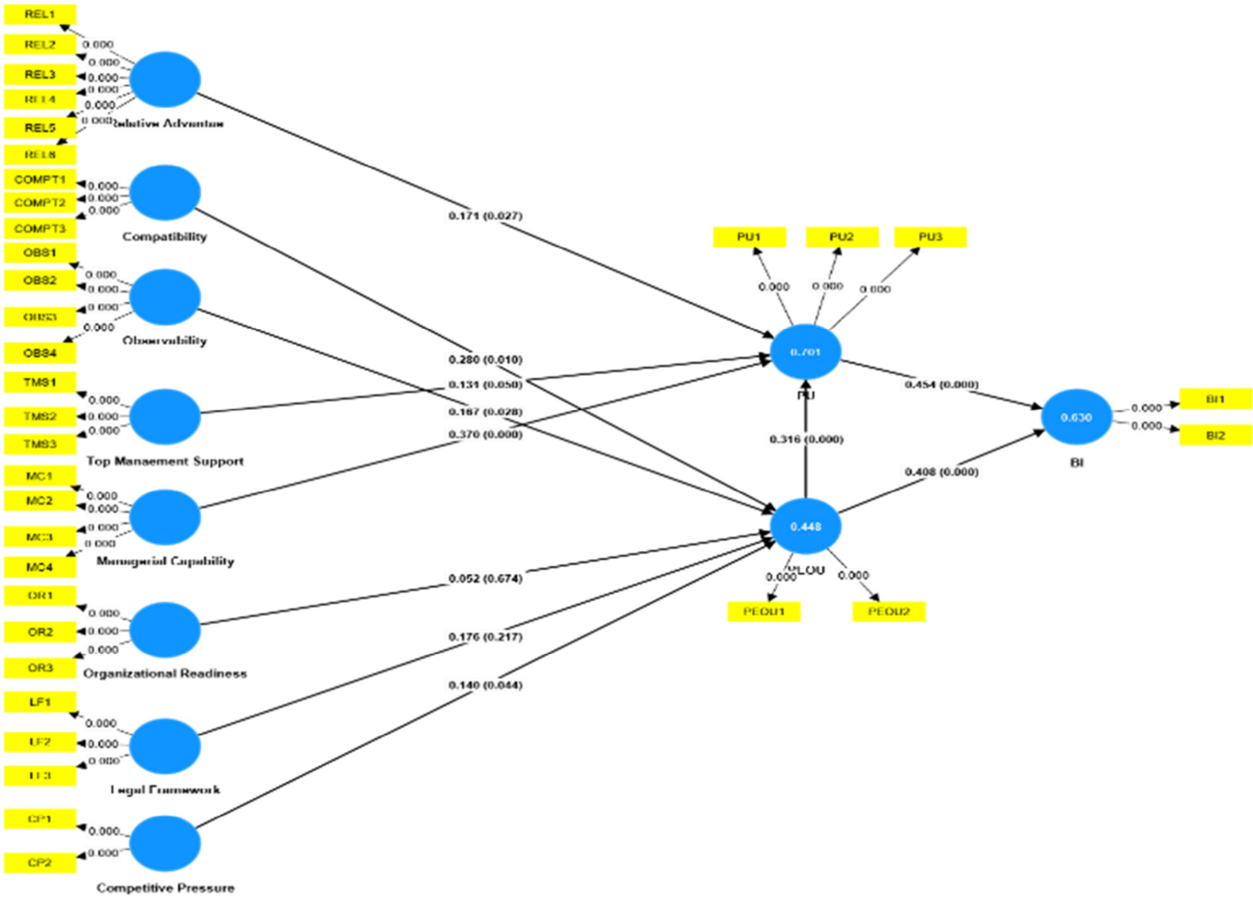

Fig. 3. The structural model.

TABLE VIII. PATH COEFFICIENT AND P-VALUES

Relation	B-value	P-value	Result
Relative Advantage → PU	0.171	0.027	H1 supported
Compatibility → PU	0.280	0.010	H2 supported
Observability → PEOU	0.167	0.028	H4 supported
Complexity → PEOU	Could not be investigated due to reliability and validity reasons		
Top Management Support → PU	0.131	0.050	H5 inconclusive
Managerial Capability → PU	0.370	0.000	H6 supported
Organizational Readiness → PEOU	0.052	0.674	H7 Not supported
Legal Framework → PEOU	0.176	0.217	H8 Not supported
Competitive Pressure → PEOU	0.140	0.044	H9 Supported
PEOU → PU	0.316	0.000	H10 Supported
PU → BI	0.454	0.000	H11 Supported
PEOU → BI	0.408	0.000	H12 Supported

IV. DISCUSSION

The current study examined the factors affecting the employees' perceptions toward adopting AI in the Palestinian government. As portrayed in Table VIII, H1, H2, H4, H6, H9, H10, H11, and H12 were found to be supported. However, H3 could not be investigated as it was excluded from the model due to reliability and validity reasons. Also the P-value of H5 is 0.05, which equals the significance level, so it was not possible to conclude this hypothesis. On the other hand, H7 and H8 were not supported.

More specifically, the results posited that relative advantage has a positive and significant impact on PU, therefore H1 is supported. This assertion is demonstrated by the case study in [26], which emphasizes this relation in Online Learning Environment context. Moreover, these results align with the findings of the research in [21], which explored the relationship between technological factors, like relative advantage and PU, in block-chain technology. The study revealed a close connection between relative advantage and PU and supposed that if employees are already aware of the benefits of new technology, it is clear that the technology is helpful.

Results indicated a positive significant relationship between Compatibility and PEOU, and hence, H2 is supported. This result is consistent with previous studies on adopting new technologies, like Haptic Enabling Technology in [54]. This outcome is realistic due to the fact that users' perception of how easy it is to use new technology is impacted by how it is compatible with current technologies in use. This result ensures that employees would find it difficult to adopt AI in the government if it is not compatible with IT infrastructure, government strategies, or its values.

Since complexity was dropped from the model for the model criteria to be enhanced, H3 was not examined in this study and it is recommended to be used in future researches to check the significance of this hypothesis.

Observability positively impacts the PEOU of AI adoption in government. So, H4 is supported, which is in line with the study in [31], where TAM was employed to identify the factors influencing the use of e-money card and confirmed the positive impact of observability on PEOU. This means that workers would perceive a new technology like AI as being simple to use if they could observe other organizations utilizing it successfully, if they could see government knowledge being shared and AI tools being demonstrated, or if they could receive AI training. On the other hand, workers would have a negative opinion of AI use in the government if it was perceived as being strange or unobservable.

It was not possible to conclude if top management support has a significant impact on the PU of AI in government. Therefore, H5 is inconclusive, while the same argument applied to H3 in terms of the need for further future investigation can be also applied here. However, authors in [20] conclude in favor of supporting H5. This is attributed to the fact that top management's efforts in communication, and resource allocation would give employees the impression that the government recognizes the benefits of adopting AI, which would increase their perception of the technology's usefulness.

H6 is supported, since managerial capability significantly influences PU. The idea is that when managers possess the skills necessary to implement new technology successfully, this would create a perception in the minds of employees, according to which this new technology is beneficial for them [22, 55]. For example, when managers possess the necessary knowledge of contemporary technologies like AI, this will create a culture of seeking out and using this technology. Additionally, when workers witness the resources that their managers are allocating to the adoption of AI, their perception will be toward acknowledging the usefulness of such a new technology [56].

Surprisingly, there is not a significant relationship between organizational readiness and PEOU, therefore H7 is not supported and this finding contradicts with the previous research in [57]. This may be because of the sample utilized in this research. In addition, users will find the technology difficult to use (low PEOU) if it lacks the required resources and high-quality data. These circumstances could act as roadblocks to its uptake and prevent the technology from being correctly implemented.

An organization's level of preparedness to implement new technologies is known as its organizational readiness [58]. This covers the culture of innovation within the organization as well as employee access to pertinent resources and competencies. Because organizational readiness affects how people view a user-friendly system, it has significant implications for PEOU.

The relationship between the legal framework and PEOU is also insignificant. Hence, H8 is not supported. This contradicts with the study in [59] on learning management system adoption. The complexity of the laws governing the field of study could be the root of the problem. Regulations and legal requirements can be convoluted and challenging to comprehend. The impact of the legal framework on user perception of ease of use may be hidden by this complexity. This implies that users may wind up concentrating more on the legal concerns surrounding a given technology than on how simple it is to use.

It should be highlighted that a person's perspective or attitude toward the law is private. Some users might not think that this has a direct impact on how they perceive usability. Since people have different opinions and values that they consider before other issues, the effect of the legal framework on PEOU may, therefore, be less significant.

The findings indicate that PEOU's attitude toward the use of AI in government is significantly and favorably impacted by competitive pressure, and thus H9 is supported. This is a reasonable conclusion also drawn by earlier research, such as that in [60], on using Internet of Things (IoT) in libraries. This is because employees would perceive AI as being easy to use and would be more approving of its utilization if they considered that the pressure from the government to adopt AI was accepted by other institutions. Additionally, every institution would strive to make a new technology easier to use if there was competitive pressure to adopt it.

Other earlier TAM researches are supported by the results, demonstrating the significant and beneficial relationships between these three TAM factors, PU, PEOU, and BI, as proposed in [16]. In this particular context, it can be asserted that the perception of ease of use of AI adoption by employees would have an impact on the perceived usefulness of AI adoption. According to the same reasoning, behavioral intentions to use AI would increase if it was perceived as helpful and easy to use. Hence, H10, H11 and H12 are supported.

V. CONCLUSIONS

This study explores the factors influencing individuals' adoption of Artificial Intelligence (AI) in the public sector, using a hybrid Technology Organization Environment - Technology Acceptance Model (TOE-TAM). The results suggest that individual intention is more complex than previously thought, and researchers should analyze it from a wider demographic perspective. This research examines technology, organization, and external factors related to AI readiness. The research provides the implications for governments and organizations considering AI adoption, emphasizing the need for training, clear strategies, and reliable data. It also aims to increase knowledge and awareness about AI implementation in Palestine. While the TOE-TAM model is useful, it has limitations related to AI knowledge, and factors like studied generalizability, and sample size. Appropriate study design and careful selection can mitigate these weaknesses. Governments should implement AI to enhance operations and address ethical, data security, and privacy concerns. This requires training, infrastructure investment, and a policy framework. Public-private collaboration and robust data governance are crucial for the successful AI adoption. Future research should use larger samples, consider additional factors like social effects, and thoroughly examine construct relationships. Both P-values and path coefficients are important when analyzing these relationships.

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