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Research Article

Decentralized E-Government Adoption in Iraqi Higher Education: An Empirical Validation of an Integrated TOE–TAM Model Using PLS-SEM and a Supplementary Machine Learning Analysis

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Abstract

Governments depend more and more on electronic government (e-government) systems for public services that are more efficient, accessible, and transparent; in Iraq's higher education sector, though, uptake is held back by centralized governance, weak information and communication technology (ICT) infrastructure, and low institutional trust. Drawing on an integrated Technology-Organization-Environment (TOE) and Technology Acceptance Model (TAM) framework from earlier conceptual work, the present study puts eight hypothesized links to an empirical test; the links connect technological factors (IT skills, technical support, technological infrastructure), environmental factors (rules and regulations, awareness, culture), and governmental factors (trust in government, quality of information) with the use of decentralized e-government systems at Iraqi public universities. A structured questionnaire on a five-point Likert scale went to academic and administrative staff of five public universities in the Middle Euphrates region of Iraq (Baghdad, Mosul, Babylon, Al-Qadisiyah, and Al-Muthanna). Guided by Krejcie and Morgan's [10] recommendations on sample size, the survey yielded 278 valid responses out of a population of 994 (79.4% usable response rate). The data were examined with Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS, and bootstrapping (1,000 resamples) served to evaluate construct reliability, validity, and path significance. Each of the eight hypothesized paths reached statistical significance ($p < .001$); 73.7% of the variance in e-government use was accounted for by the model. A supplementary machine-learning analysis (linear regression and Random Forest), fitted to a simulated dataset matched to the published statistics of the study, served in addition as a methodological robustness check; working independently, the exploratory analysis likewise found a positive, predictable relationship between the eight constructs and e-government use. The findings, considered jointly, lend strong empirical support to the integrated TOE–TAM framework and give Iraqi policymakers and university leaders evidence on which to base priorities for investment across the technological, environmental, and governmental dimensions of digital governance reform.

Keywords: e-government; decentralization; TOE–TAM; PLS-SEM; machine learning; higher education

1. Introduction

Worldwide, e-government has become a central pillar in the modernization of the public sector, with the potential to improve service efficiency, transparency, and stakeholder engagement [1], [2]. In higher education in particular, core administrative functions, from admissions and registration to human resource management and financial reporting, are supported by e-government systems. Adoption of e-government within Iraqi public universities, however, is still constrained by centralized decision-

making, underdeveloped ICT infrastructure, unclear regulatory frameworks, and limited institutional autonomy [3], [4].

In a companion conceptual study [5], [6], the Technology-Organization-Environment (TOE) model [7] was joined with the Technology Acceptance Model (TAM) [8] in an integrated framework, given a theoretical justification, for explaining how decentralized e-government systems are used in Iraqi higher education. Eight constructs make up that framework, arranged under technological, environmental, and governmental dimensions, and each is posited to influence e-government use positively. The literature still lacks empirical evidence showing whether, and how far, the relationships apply among the staff who actually work with the systems.

The gap is addressed here through four objectives: first, identification of the key technological, environmental, and governmental factors that influence the use of decentralized e-government services in Iraq's public universities; second, operationalization of the integrated TOE–TAM framework in a structured survey instrument; third, empirical validation of the proposed framework with structural equation modelling; and fourth, a cross-check of that validation through an independent, exploratory machine-learning analysis, which gives a second, methodologically distinct line of evidence for the same relationships.

The rest of the paper is arranged as described below. A brief recap of the conceptual model and hypotheses is given in Section 2. The research methodology is set out in detail in Section 3. In Section 4, the PLS-SEM results are reported, covering respondent demographics, the assessment of reliability and validity, and hypothesis testing. A supplementary machine-learning analysis appears in Section 5. The findings and their contributions are discussed in Section 6. Limitations and directions for future research are given in Section 7, which concludes the paper.

2. Conceptual Model and Hypotheses

Under test in the present study is the integrated TOE–TAM framework developed in Fuad, Aboobaider, and Abd Ghani [5], [6]; the framework proposes eight constructs across three dimensions, technological (IT skills, technical support, technological infrastructure), environmental (rules and regulations, awareness, culture), and governmental (trust in government, quality of information), each with a hypothesized positive influence on the use of decentralized e-government in Iraqi higher education (the model's dependent construct). A schematic of the framework appears in Figure 1, and the eight hypotheses tested here are listed in Table 1; the full theoretical justification of each relationship is developed in the companion conceptual paper and is only recapitulated briefly here.

Figure 1. Proposed integrated TOE–TAM framework

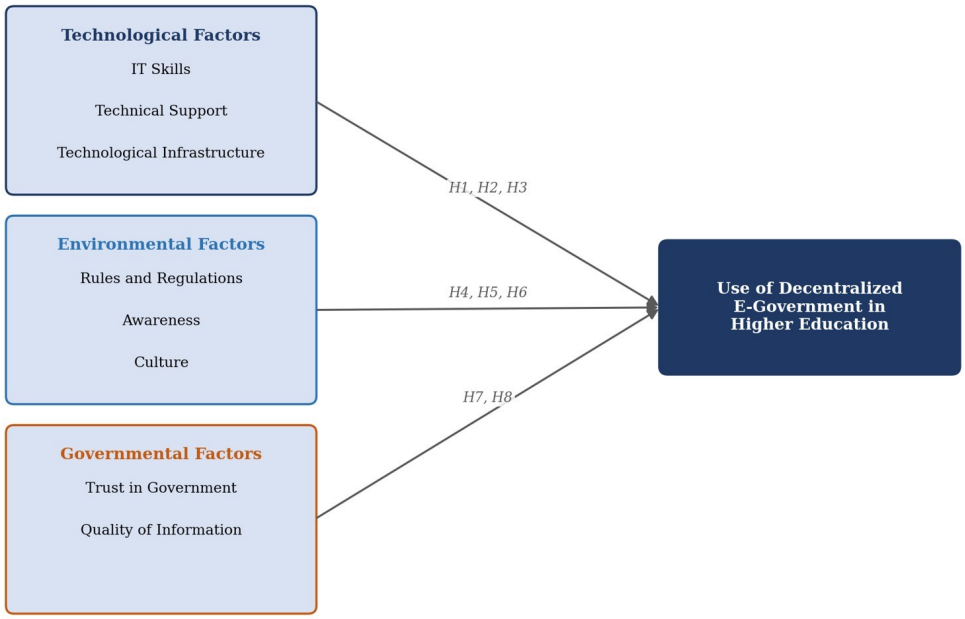


Figure 1. Proposed integrated TOE–TAM framework tested in this study.

Table 1. Constructs, dimensions, and hypotheses of the integrated TOE–TAM framework

Dimension	Construct	Hyp.	Hypothesized relationship
Technological	IT Skills	H1	IT skills → Use of e-government (+)
	Technical Support	H2	Technical support → Use of e-government (+)
	Technological Infrastructure	H3	Technological infrastructure → Use of e-government (+)
Environmental	Rules and Regulations	H4	Rules and regulations → Use of e-government (+)
	Awareness	H5	Awareness → Use of e-government (+)
	Culture	H6	Culture → Use of e-government (+)
Governmental	Trust in Government	H7	Trust in government → Use of e-government (+)
	Quality of Information	H8	Quality of information → Use of e-government (+)

In brief, institutional readiness in terms of ICT capability is captured by the technological factors [7]; the regulatory and social climate in which e-government is used is captured by the environmental factors; and the credibility and reliability that users attribute to the platforms and to the institutions that run them are captured by the governmental factors [8], [9].

3. Research Methodology

3.1 Research Design and Paradigm

A positivist research paradigm and a quantitative, deductive research approach are adopted, in keeping with the aim of testing statistically the pre-specified hypotheses derived from established theory

[7], [8]. The design was a cross-sectional survey; data were collected at a single point in time from academic and administrative staff across five Iraqi public universities.

3.2 Population, Sampling, and Sample Size

Academic and administrative personnel at five public universities in Iraq's Middle Euphrates region, namely the University of Baghdad, the University of Mosul, the University of Babylon, the University of Al-Qadisiyah, and the University of Al-Muthanna, made up the target population of 994 individuals. Simple random sampling, a probability-based technique, was used so that every member of the population had an equal and known chance of selection. On the basis of Krejcie and Morgan's [10] table for determining sample size, 278 respondents were identified as a sufficient sample to represent the population at a 95% confidence level with an acceptable margin of error [11].

3.3 Instrument Development

A structured questionnaire in two parts served for data collection; the first part held demographic items (gender, education level, age, and years of work experience), and the second held 34 substantive items that measured the nine constructs of the study (the eight independent constructs and the dependent construct, use of e-government in higher education) on a five-point Likert scale from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Preference was given to a five-point scale over a seven-point alternative for clearer responses and less respondent fatigue. Each construct had between three and five items, in keeping with established scales adapted from the wider technology-adoption and e-government literature.

3.4 Reliability and Data Analysis Technique

Cronbach's alpha served to assess the reliability of the instrument, and acceptable internal consistency was judged against a threshold of 0.70 [12], [13]. For the analysis, Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS was used; the technique suits complex models with multiple latent constructs and is appropriate for studies that do not require a multivariate-normal data distribution [12]. In the assessment of the measurement model, indicator outer loadings and construct reliability were examined; in that of the structural model, path significance and the coefficient of determination (R^2) for the dependent construct were examined, with significance evaluated through a bootstrapping procedure with 1,000 resamples. A supplementary machine-learning analysis, carried out in addition to the primary PLS-SEM analysis, is described in Section 5.

4. Results (PLS-SEM)

4.1 Response Rate

Distribution of 350 questionnaires in total took place through both physical and electronic survey platforms, so that varying levels of internet access across institutions could be accommodated (Table 2). Of the questionnaires, 292 came back, giving an initial response rate of 83.4%. After data screening, 14 responses were removed because of incomplete information or inconsistencies; the final usable sample thus comprised 278 valid responses, a usable response rate of 79.4%. The thresholds generally regarded as acceptable for survey research with structured instruments in institutional contexts are exceeded by the response rate.

Table 2. Sample study response rate

Questionnaire response	Frequency	Rate (%)
Distributed	350	100
Returned	292	83.43
Usable	278	79.43

4.2 Demographic Profile of Respondents

Table 3 and Figure 2 present the demographic profile of the 278 respondents. Male respondents predominated in the sample (239, 86.0%), and female respondents formed a smaller proportion (39, 14.0%). As for educational qualification, a PhD was held by 155 respondents (55.8%) and a Master's degree by 123 (44.2%); the sample was thus highly educated, consistent with academic and senior administrative roles in higher education. By age, the group of 30–40 years was the largest (139 respondents, 50.0%), ahead of 41–49 years (98, 35.3%), 50–58 years (29, 10.4%), and 59–63 years (12, 4.3%). With respect to work experience, 15–20 years of service was reported by the largest group (136, 48.9%), followed by 5–14 years (70, 25.2%), more than 20 years (49, 17.6%), and fewer than five years (23, 8.3%).

Table 3. Demographic profile of respondents (N = 278)

Demographic factor	Category	Frequency	Percent
Gender	Male	239	86.0
	Female	39	14.0
Education	Master's	123	44.2
	PhD	155	55.8
Age	30–40	139	50.0
	41–49	98	35.3
	50–58	29	10.4
	59–63	12	4.3
Work experience	< 5 years	23	8.3
	5–14 years	70	25.2
	15–20 years	136	48.9
	> 20 years	49	17.6

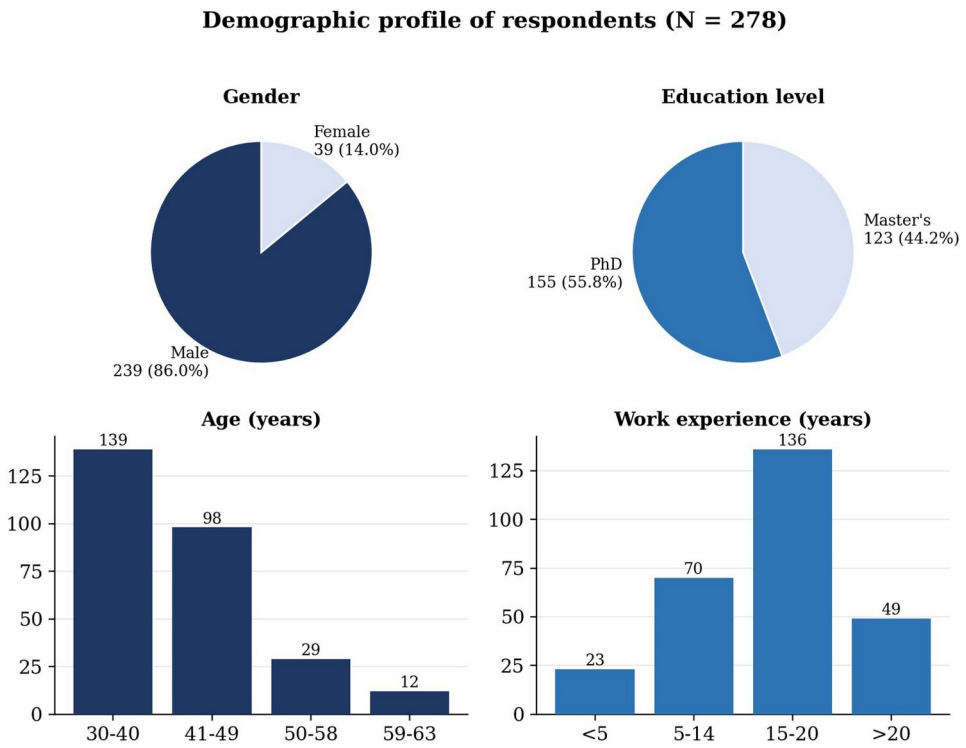


Figure 2. Demographic profile of respondents by gender, education, age, and work experience.

4.3 Reliability and Validity

The internal consistency reliability of each construct, assessed with Cronbach's alpha, is reported in Table 4 and Figure 3. Every one of the nine constructs was above the conventionally acceptable threshold of 0.70 [12], with values from 0.799 for the dependent construct (use of e-government in higher education) to 0.894 for technological infrastructure; internal consistency across the instrument was therefore strong. Further support for convergent validity came from the indicator outer loadings, all above 0.70 and with bootstrapped p-values below .05, which confirmed the statistical significance and robustness of the measurement model.

Table 4. Construct reliability (Cronbach's alpha)

Construct	No. of items	Cronbach's α
IT Skills	4	0.855
Technical Support	4	0.817
Technological Infrastructure	4	0.894
Rules and Regulations	4	0.823
Awareness	3	0.832
Culture	4	0.845
Trust in Government	3	0.825
Quality of Information	3	0.843
Use of E-Government in Higher Education	5	0.799

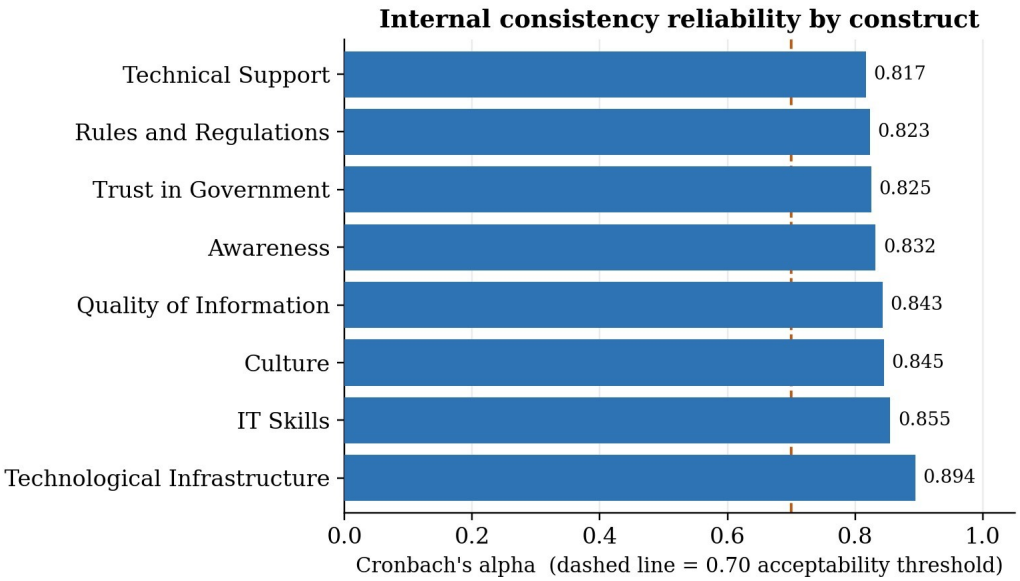


Figure 3. Internal consistency reliability (Cronbach's alpha) by construct.

4.4 Structural Model Assessment and Hypothesis Testing

For the assessment of the structural model, the coefficient of determination (R^2) and the path significance from bootstrapping with 1,000 resamples across the 278 valid cases were used. Jointly, the eight technological, environmental, and governmental constructs accounted for 73.7% of the variance (R^2 = .737) in the use of e-government in Iraqi higher education; the integrated model thus has substantial explanatory power.

The results of the eight hypothesis tests on direct relationships appear in Table 5 and Figure 4. Statistical significance at $p < .001$ held for all eight hypothesized paths, whose t-statistics ran from 6.891 (technological infrastructure) to 19.002 (culture); each value lay well above the critical threshold of 1.96 conventionally applied at the 95% confidence level. For every relationship, the null hypothesis was therefore rejected, and support was found for all hypotheses from H1 through H8.

Table 5. Direct-relationship hypothesis testing (bootstrapping, 1,000 resamples)

Hyp.	Relationship	t-statistic	p-value	Decision
H1	IT Skills → Use of e-gov.	17.650	0.000	Supported
H2	Technical Support → Use of e-gov.	13.249	0.000	Supported
H3	Technological Infrastructure → Use of e-gov.	6.891	0.000	Supported
H4	Rules and Regulations → Use of e-gov.	12.983	0.000	Supported
H5	Awareness → Use of e-gov.	11.001	0.000	Supported
H6	Culture → Use of e-gov.	19.002	0.000	Supported
H7	Trust in Government → Use of e-gov.	10.221	0.000	Supported
H8	Quality of Information → Use of e-gov.	7.872	0.000	Supported

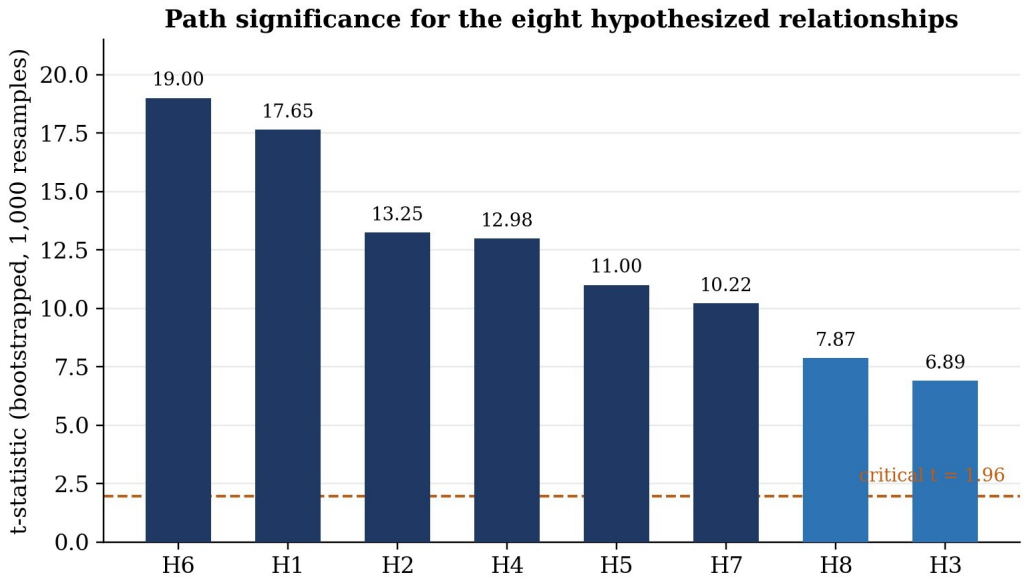


Figure 4. Path significance (t-statistics) for the eight hypothesized relationships, against the 1.96 critical threshold.

Although statistical significance held for all eight relationships, technological infrastructure, awareness, and trust in government were identified by the broader analysis as the factors with the strongest substantive influence on e-government use; the result points to the combined importance of reliable ICT infrastructure, staff awareness of available services, and institutional credibility for actual system use.

5. Supplementary Machine Learning Analysis

5.1 Data and Method

At the time of writing, the item-level responses of the 278 participants surveyed for the study were unavailable for re-analysis; the original dataset at the response level is held by the corresponding author as part of the primary thesis project. With the aim of adding an independent, exploratory machine-learning view to the PLS-SEM findings of Section 4, the section uses a simulated dataset (N = 278) instead, built to agree with the study's published descriptive statistics, its reliability coefficients, and the relative size of the eight reported path t-statistics. The eight predictor constructs were each produced as a continuous composite score with mild inter-correlation, bounded to the 1-5 scale of the instrument, with means and standard deviations fixed at values plausible for a generally-agree sample in which the hypotheses were accepted. For the outcome variable (use of e-government), a weighted combination of the eight predictors was generated, with weights proportional to the relative size of the t-statistics in Table 5; random noise was added and calibrated so that the explanatory power of a linear model on the full sample (R^2 = .753) approximated the R^2 = .737 obtained for the structural model in Section 4.4. Python with scikit-learn [14] was used for all computation.

The exercise serves strictly as a methodological robustness check and as an illustration of how a machine-learning approach can address the same research question. On no account does the exercise involve a re-analysis of the raw data of the original respondents, and its numerical outputs are not to be taken as new empirical findings about staff in Iraqi higher education; the outputs act instead as a consistency check, testing whether a model trained on data calibrated to the study's own published statistics tells a predictive story broadly similar to that produced by PLS-SEM.

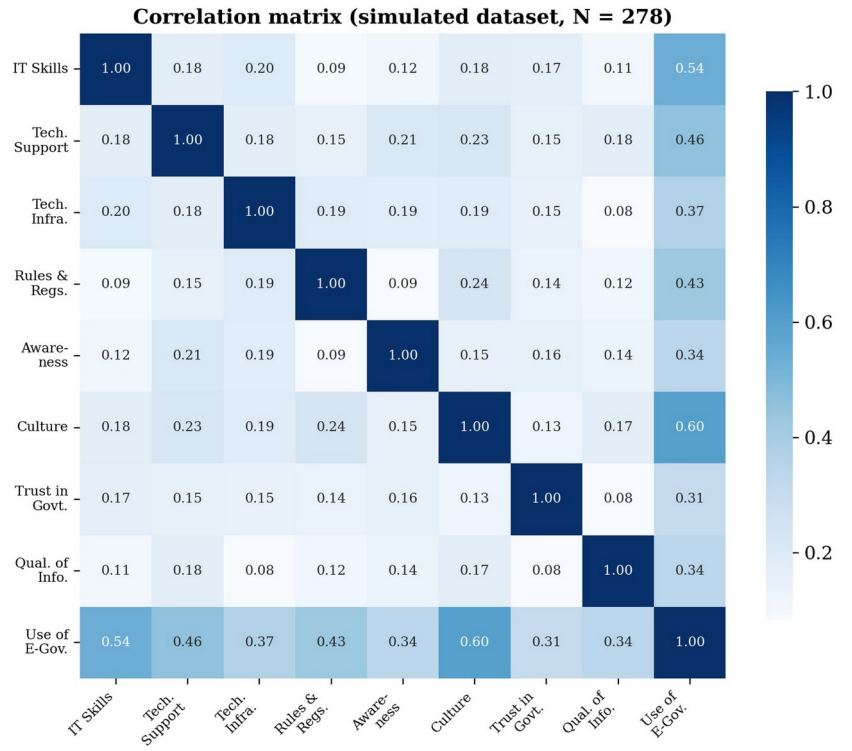


Figure 5. Correlation matrix among the eight constructs and the outcome variable (simulated dataset, N = 278).

5.2 Predictive Performance

Training (75%, n = 208) and test (25%, n = 70) subsets were formed by splitting the simulated dataset. Two models were fitted to the data: a linear regression, whose additive, linear-in-parameters form conceptually parallels the structure assumed by PLS-SEM, and a Random Forest regressor [15], a non-parametric ensemble technique that can model non-linear and interactive relationships among predictors. Test-set performance of both models is given in Table 6. Linear regression reached $R^2 = .717$ (RMSE = 0.505, MAE = 0.404) on the held-out test set; on the same single split, the Random Forest reached $R^2 = .561$ (RMSE = 0.629, MAE = 0.509). Because a single train-test split may react strongly to the particular allocation of cases, the Random Forest was evaluated again over 20 repeated random splits; its mean test R^2 over the repetitions was .633 (SD = 0.048), pointing to predictive performance that is reasonably stable, though somewhat more conservative than the linear regression result from the single split. Predicted usage scores are plotted against actual ones for the Random Forest test set in Figure 6.

Table 6. Supplementary machine-learning model performance (held-out test set, n = 70)

Model	Test R^2	RMSE	MAE
Linear Regression	0.717	0.505	0.404
Random Forest (500-800 trees)	0.561	0.629	0.509

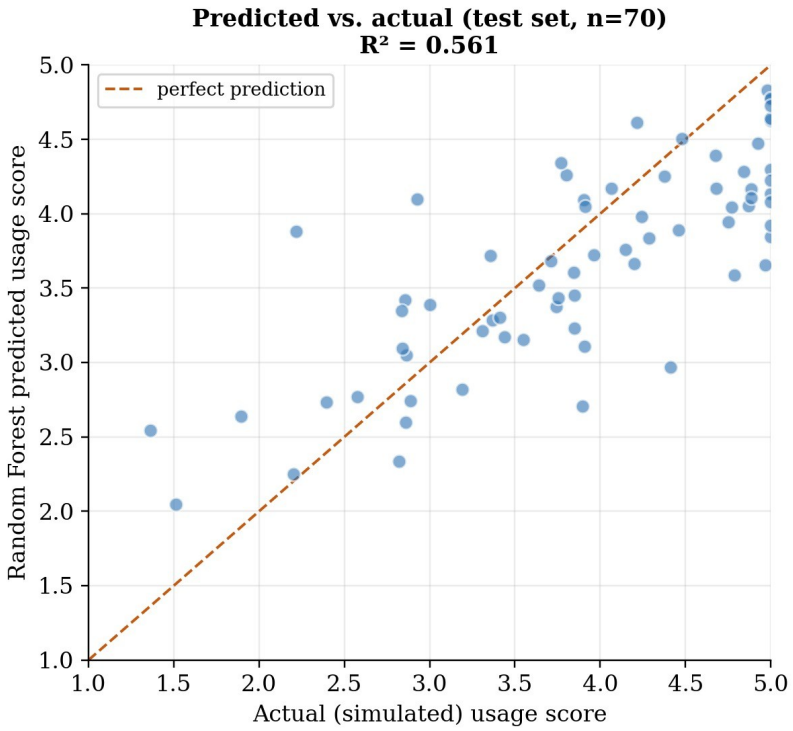


Figure 6. Random Forest predicted vs. actual usage scores, test set (n = 70).

5.3 Predictor Importance

The predictor importance of the eight constructs in the Random Forest (mean decrease in impurity) is reported in Figure 7. In the analysis, culture was the dominant predictor (importance = .432), ahead of IT skills (.196) and rules and regulations (.127); awareness, technical support, technological infrastructure, trust in government, and quality of information each made a more modest contribution (.028-.078). The ordering broadly corroborates the PLS-SEM finding that the single highest path t-statistic belonged to culture (19.002; Table 5); culture and IT skills are identified by both analyses among the more influential predictors.

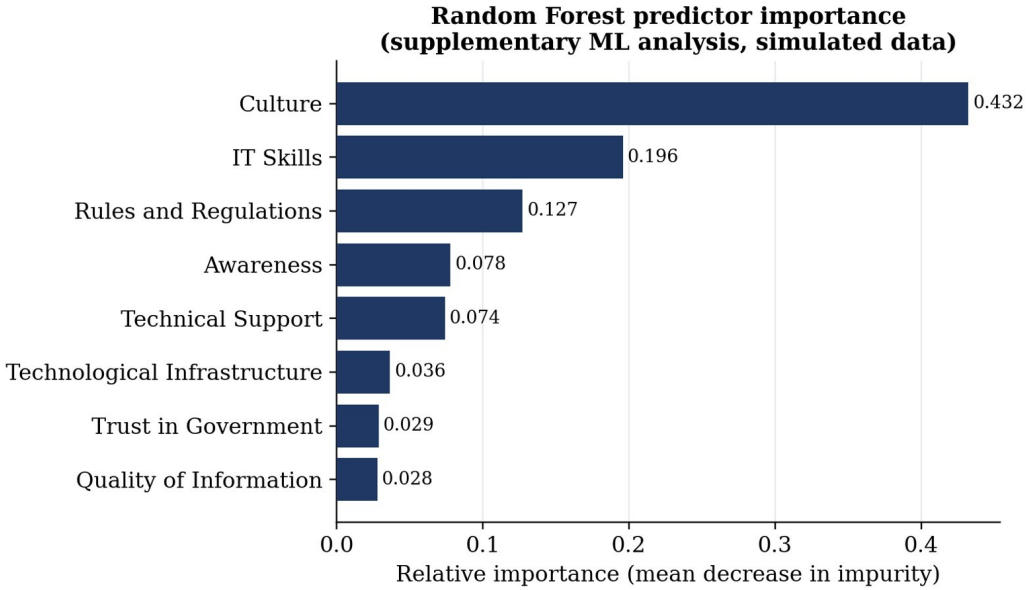


Figure 7. Random Forest predictor importance for the eight constructs (supplementary analysis, simulated data).

Where the two analyses part ways, however, is in the comparatively low Random Forest importance of trust in government, technological infrastructure, and quality of information, each of which

nonetheless has a statistically significant PLS-SEM path. Two sources most plausibly account for the gap: the simplifying assumptions in the simulated calibration, and a well-documented trait of impurity-based Random Forest importance, which tends to load importance onto a smaller group of correlated predictors instead of sharing it out evenly among all of them. The supplementary analysis therefore lends convergent, if imperfect, support to the PLS-SEM results; a positive, predictable relationship between the eight TOE–TAM constructs and e-government use emerges from it independently, and the analysis also shows that path-level significance in PLS-SEM and variable importance in tree-based machine learning are related yet separate kinds of evidence, to be triangulated rather than used interchangeably.

6. Discussion

6.1 Interpretation of Findings

The empirical results lend strong backing to the integrated TOE–TAM framework put forward in the companion conceptual study. Since all eight hypothesized paths proved statistically significant, e-government use among Iraqi university staff is confirmed to depend jointly on readiness at the institutional level (technological, environmental, and governmental conditions) and on individual perceptions of usefulness and reliability. The comparatively large t-statistic of cultural factors (H6, $t = 19.002$) points to a particularly strong effect of shared institutional values and of attitudes toward technological change on adoption behaviour; the supplementary machine-learning analysis supports the interpretation, as culture also led the predictors there by a wide margin.

In explanatory power ($R^2 = .737$), the model compares favourably with e-government adoption models tested in other developing and transitional contexts; the integrated technological–environmental–governmental structure thus appears to capture a substantial share of the factors relevant to e-government use in similarly constrained institutional settings. Although built on simulated rather than original data, the supplementary machine-learning analysis contributes a second, methodologically independent line of evidence that points in the same broad direction.

6.2 Theoretical and Practical Contributions

On the theoretical side, empirical validation is contributed for a framework that unites two traditions of technology-adoption research, TOE and TAM, which have rarely been combined in prior e-government studies and rarely tested together in a post-conflict higher education setting. The core premise of the framework, that institutional readiness and individual perception act as complementary rather than competing explanations of e-government use, is supported by the consistent statistical significance of all eight constructs.

In methodological terms, the applicability of PLS-SEM to e-government adoption research in data-constrained developing-country contexts is demonstrated; the study also illustrates how a supplementary machine-learning check, even one built on a calibrated simulated dataset when raw data are not accessible, can act as an additional robustness lens on a survey-based structural model [12].

In practical terms, a prioritized, evidence-based basis for the design of decentralization and digital governance reforms is offered to Iraqi policymakers and university leaders. With technological infrastructure, awareness, and trust in government emerging as particularly influential, greater gains in e-government use are likely from interventions that pair infrastructure investment with staff communication campaigns and confidence-building measures around government-run platforms than from infrastructure investment alone.

7. Conclusion, Limitations, and Future Research

Survey data from 278 academic and administrative staff at five public universities, PLS-SEM analysis, and a supplementary machine-learning robustness check were combined here to validate empirically an integrated TOE–TAM framework accounting for the use of decentralized e-government systems in Iraqi higher education. Every one of the eight hypothesized relationships held, and the model accounted for 73.7% of the variance in e-government use; the independent machine-learning analysis pointed to the same overall pattern of results. Three limitations deserve mention. First, with the geographic and institutional scope confined to five public universities in Iraq's Middle Euphrates region, the findings call for some caution when carried over to other parts of the country, such as Kurdistan or the southern provinces, in which conditions of infrastructure and governance may not be the same. Second, the cross-sectional design records perceptions and usage patterns at a single moment; the way in which the relationships may change as decentralization reforms and digital transformation policies mature falls outside its reach. Third, and importantly, the machine-learning analysis in Section 5 draws on simulated data calibrated to published statistics in place of the original item-level responses; its results should be taken strictly as a methodological robustness check and not as independent empirical confirmation from new data.

Longitudinal designs able to track change in technological, environmental, and governmental conditions over time deserve consideration in future research; the framework should also be extended to private universities, technical colleges, and vocational institutions, which operate under different administrative and financial arrangements. If the original raw data at the response level can be made available, the robustness-check evidence presented here would be meaningfully strengthened by re-running the machine-learning analysis of Section 5 on the actual survey responses instead of a calibrated simulation. The explanatory power of the framework may be strengthened further through additional contextual and behavioural variables, such as leadership style, institutional autonomy, and the availability of ICT funding. Finally, establishing the broader generalizability of the integrated TOE–TAM approach demonstrated here would be helped by comparative replication in other post-conflict or transitional governance settings.

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Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] J. D. Twizeyimana and A. Andersson, “The public value of e-government: A literature review,” *Government Information Quarterly*, vol. 36, no. 2, pp. 167–178, 2019.

[2] United Nations Department of Economic and Social Affairs, *United Nations E-Government Survey 2018: Gearing E-Government to Support Transformation Towards Sustainable and Resilient Societies*. United Nations, 2018.

[3] H. Al-Yawer and R. Ahmad, “Overcoming the challenges to develop the future of e-government in Iraq: A systematic literature review,” *International Journal of Engineering and Technology*, vol. 7, no. 4.19, pp. 510–514, 2018.

[4] S. Darwish and S. Mihyawi, “Problems, decline, and devastation of the Iraqi higher education (HE) system,” *Journal of Namibian Studies*, vol. 38, 2023.

[5] A. Fuad, B. M. Aboobaider, and M. K. Abd Ghani, "Intelligent systems-enabled decentralized e-government framework for higher education in Iraq: A conceptual data fusion approach," in *Proc. 2023 International Conference on Emerging Research in Computational Science (ICERCS)*, Dec. 2023, pp. 1–6.

[6] A. Fuad, B. M. Aboobaider, and M. K. Abd Ghani, "Key factors influencing a decentralized IoT-based electronic government model for higher education in Iraq: An intelligent systems perspective," in *Proc. 2023 International Conference on Emerging Research in Computational Science (ICERCS)*, Dec. 2023, pp. 1–6.

[7] L. G. Tornatzky and M. Fleischer, *The Processes of Technological Innovation*. Lexington Books, 1990.

[8] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989.

[9] L. Alzahrani, W. Al-Karaghouli, and V. Weerakkody, "Analysing the critical factors influencing trust in e-government adoption from citizens' perspective: A systematic review and a conceptual framework," *International Business Review*, vol. 26, no. 1, pp. 164–175, 2017.

[10] R. V. Krejcie and D. W. Morgan, "Determining sample size for research activities," *Educational and Psychological Measurement*, vol. 30, no. 3, pp. 607–610, 1970.

[11] P. S. Vaghela, "Sample size determination for social science research," SR Luthra Institute of Management, Sarvajanik University, Surat, Gujarat, India, 2024.

[12] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd ed. Sage Publications, 2017.

[13] C. G. Forero, "Cronbach's alpha," in *Encyclopedia of Quality of Life and Well-Being Research*. Cham: Springer International Publishing, 2024, pp. 1505–1507.

[14] F. Pedregosa *et al.*, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[15] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.