Exploring the Factors Influencing Information Technology Adoption in Manufacturing Economies During Conflict: Evidence from Iraq's Manufacturing Sector

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Abstract

Background: Background in Information technology (IT) integration is still unexplored as it adds to manufacturing performance in the post-conflict emergent economies. Iraq is a unique situation: though with the fifth-largest known oil deposits in the world and the long-established industrial infrastructure Iraq has historically been a manufacturing nation, the 4-decade war and the resulting institutional instability after the war in 2003 severely affected the manufacturing industry. These institutional features make traditional IT-adoption models, which were designed to work in stable institutional settings somewhat inapplicable in this case.

Purpose: This research seeks to understand the direct relationship between three key technological characteristics based on Diffusion of Innovations (DOI) theory which consist of Perceived Relative Advantage, Technology Compatibility and Technology Complexity, and level of IT adoption with Iraqi manufacturing performance in the industrial firms.

Methodology: The cross-sectional design of the quantitative design was used. The stratified random sampling gave a selective maximum of 285 useful responses of the registered Iraq manufacturing companies. Smart-PLS 4.0 was used to conduct a test on a parsimonious three-predictor model of IT adoption and its downstream performance associations where firm size was used as a moderating variable.

Findings: The outcome showed that the Perceived Relative Advantage and Technology Compatibility both had positive impact on the level of IT Adoption, whereas Technology Complexity had a strong negative impact. All these technology characteristics accounted for a significant percentage of the variance in IT adoption. Besides, IT adjected Level was identified as a solid positive predictor of Manufacturing Performance, firm size moderated this speculation, suggesting that larger firms are likely to enjoy more performance benefits by adopting IT over their smaller counterparts.

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Implications: The validated, parsimonious technology-characteristics model provides reproducible effect-size benchmarks for post-conflict manufacturing environments. Findings offer practical guidance to Iraqi industrial policymakers and firm managers on technology-attribute-specific interventions to accelerate IT-enabled manufacturing transformation.

Keywords: *IT Adoption; Relative Advantage; Technology Compatibility; Technology Complexity; PLS-SEM; Iraqi Manufacturing; Post-Conflict Economy; Manufacturing Performance; SMEs; DOI Theory*

1. Introduction

High speed of digitalization has changed information technology (IT) into a highly important strategic resource of manufacturing businesses, instead of an online support tool, in the world (Ghobakhloo and Iranmanesh, 2021; Zheng et al., 2021). There has been a constant precedent of positive effects in terms of productivity, quality, and responsiveness in the market with the introduction of enterprise resource planning, digital supply-chain integration, and process automation (Dalenogare et al., 2018; Singh & Garg, 2021). Nonetheless, the pace and trend of IT adoption significantly differ depending on institutional, economic and political settings, which entailed context-dependent exploration. Iraq is an example of a post-conflict economy where the conditions that precede IT adoption are very different in qualitative terms as compared to the conditions experienced in developing countries that are stable. Physical infrastructures have been eroded and planning horizons in the organizational environment condensed by four decades of armed conflict, eight years of international sanctions, and post-2003 institutional instability, phenomena that cannot be well-modelled using standard models of adoption that rely on stable institutional environments (Chatterjee et al., 2021; Ekeoma et al., 2024). At the same time, the manufacturing sector plays a strategic part in the Iraqi economic diversification plan, and it thus forms one of the top-priority areas in which an evidence-based policy can be applied. The current literature on IT adoption at the industry level is theoretically abundant and sporadic. The technological, organizational and environmental constructs are included in most of the tested models, resulting in analytically complex frameworks that are hard to operationalize in the conditions of the field resource constraints inherent in post-conflict environments (Awa et al., 2017). This limitation is addressed by the current research that proposes and tests a parsimonious model that includes three basic DOI variables (Perceived Relative Advantage, Technology Compatibility, and Technology Complexity) as first mover antecedents of IT adoption, and IT adoption is positively related to manufacturing performance.

1.1 Research Objectives and Questions

The proposed study has three goals which are: (1) to test whether the characteristics of DOI-based technology are found to be strongly correlated with the level of IT adoption in Iraqi manufacturing; (2) to test whether the level of IT adoption is strongly correlated with the outcome of the manufacturing performance; and (3) to test whether the level of production moderates the level of adoption and performance. The Research questions are:

- RQ1: Are Perceived Relative Advantage, Technology Compatibility, and Technology Complexity significantly associated with IT adoption in Iraqi manufacturing firms?
- RQ2: Is IT adoption level significantly associated with manufacturing performance?
- RQ3: Does firm size moderate the relationship between IT adoption and manufacturing performance?

2. Literature Review and Theoretical Framework

2.1 Diffusion of Innovations (DOI) Theory

Rogers (1995, 5th ed. (2003) Diffusion of innovations theory determines five perceived attributes that determine the rate of adoption: relative advantage, compatibility, complexity, trialability and observability. Among them, the three that have proved to be the most explanatory over time within the context of organization IT adoption are not discarded and are kept as theoretical frameworks of this study. Perceived Relative Advantage can be defined as the level of perceived superiority of IT to the current non-IT practices. It is the most steadfast correlate of adoption within the manufacturing and the SME settings (Singh & Garg, 2021; Zhou & Zheng, 2023). The perceived productivity benefits of IT have greater salience in post-conflict environments when the inefficiencies in operations are structural in nature. Technology Compatibility refers to the level between IT and the current processes, values and infrastructure of an organization (Awa et al., 2017). It has specific implications in the Iraqi context: inherited infrastructure limits the scope of possible IT solutions to solutions that can be integrated with the current ones. Technology Complexity is the perceived complexity of using or comprehending an IT system and has always served as a barrier to adoption particularly amongst SMEs with a lower-than-average technical human capital (Moeuf et al., 2020). This construct will have a negative coefficient in the structural model.

2.2 Resource-Based View and the Adoption–Performance Link

According to Wernerfelt (1984), as well as the later authors in the Resource-Based View (RBV), competitive performance is predetermined by internal resource endowments - technological, human and organizational. Co-deployment of IT with other associated organizational capabilities has been linked to long-term performance enhancement when IT is staged as a strategic resource (Zhang & Li, 2022). This point of view justifies the direction of H2 (IT Adoption → Manufacturing Performance) and invites H3: bigger companies, which possess more complementary resources are more likely to turn IT adoption into performance gains (Ghobakhloo and Iranmanesh, 2021; Li et al., 2022).

2.3 Conceptual framework and Hypothesis Development

This study is found on a thorough conceptual framework where the characteristics of technology are first discussed in relation to the degree of IT adoption within manufacturing companies and the effect that this feature of technology has on the manufacturing performance. The model is based on the two established aspects of theoretical foundations that are Diffusion of Innovation Theory (DOI) and the Resource-Based View Theory (RBV). There are 3 core factors of Independent Variables (Technology Characteristics): perceived Relative Advantage, Technology Compatibility, and Technology Complexity. These variables are founded on DOI Theory which assumptions is that the probability that any individual and organization will adopt any technology is determined by the perception of the good the technology brings, how well the technology has aligned with current practices, and the perceived difficulty of utilizing it. To this extent, the research hypothesizes as follows, H1a) Perceived Relative Advantage has a positive influence on the level of IT adoption, H1b) Technology Compatibility has a positive influence on the level of IT adoption and H1c) Technology Complexity has negative effect on the adoption process.

The main point of the model is the Mediating Variable (IT Adoption Level) that lies between technological features and manufacturing performance. This implies that the effects of the characteristics of technology on performance are not immediate, but rather it goes through the real level of adoption of an IT firm. This renders IT Adoption Level a significant variable in comprehending the mechanism in which technology nature translates into organizational results. The last output of the model is known as the Dependent Variable (Manufacturing Performance). Hypothesis H2: It is hypothesized that better manufacturing performance is achieved with increased levels of IT adoption. This part of this model is rooted in RBV Theory, which suggests that technological capabilities are a strategic asset which gives firms a comparative advantage, which is ultimately translated into their operational and productive performance. The

Moderating Variable (Firm size) brings an extra dimension of analysis since it introduces the firm size as a moderator between the level of IT adoption and manufacturing performance. Hypothesis H3 speculates that the firm size moderates this relationship indicating that the impact of the adoption of IT on the performance can differ based on whether firms are small, medium or large. This shows how the present research focused on the organizational context, and it is one of the ways the dynamics of the relationship under study are formed as shown in figure 1.

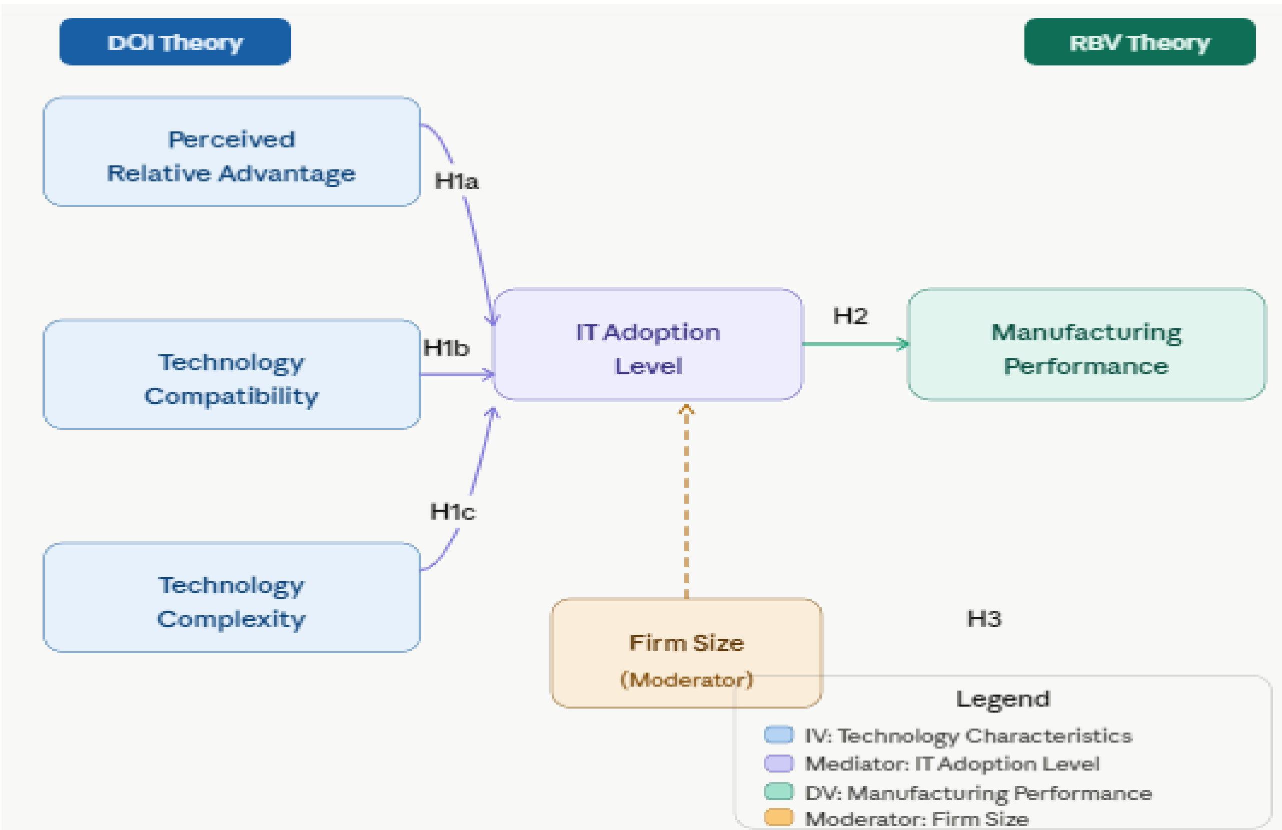

Figure 1: Conceptual framework and Hypothesis Development

3. Research Methodology

3.1 Research Design

The present research is based on a quantitative design of a cross-sectional survey and is a part of a positivist school of philosophy (Sekaran and Bougie, 2022). Since the focus of the study is to describe the current trends of IT adoption and performance correlations in the Iraqi manufacturing industry and it is not to follow a longitudinal change, a cross-sectional approach is suitable. It must be known, though, that cross-sectional information does not allow making a cause-and-effect analogy; everything they find is taken as associative information.

3.2 Population, Sampling, and Sample Size

The target unit population is registered manufacturing companies with the Ministry of Industry and Minerals in five sub-sectors, food processing, textiles and apparel, chemicals, construction materials and metal fabrication ($N \approx 2{,}400$). The stratified random sampling was used to obtain proportional representation where stratification variables were the sub-sector and firm size. Out of the 322 questionnaires given out, 285 out of the usable responses were received (response rate: 88.4). The sample is not too small as it meets the requirement and PLS-SEM 10× guideline (3 predictors × 10 = 30 minimum; Hair et al., 2022).

3.3 Measurement Instrument

A structured questionnaire operationalizes the five constructs presented in Table 1. All items are rated on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). Technological construct scales were adapted from validated DOI-based instruments (Awa et al., 2017; Rogers, 2003). Performance items follow Singh & Garg (2021) and Battistoni et al. (2023).

Table 1. Survey Structure: Technology-Focused Model

Section	Variable	Role in Model	Scale	Items
A	Perceived Relative Advantage	Independent Variable (Technological)	Likert 1–5	5
B	Technology Compatibility	Independent Variable (Technological)	Likert 1–5	4
C	Technology Complexity	Independent Variable (Technological)	Likert 1–5	4
D	IT Adoption Level	Mediator / Main Dependent Variable	Likert 1–5	8
E	Manufacturing Performance	Dependent Variable	Likert 1–5	8
F	Firm Size	Moderator (dummy-coded: Small=0, Medium=1, Large=2)	Categorical	1

3.4 Validity and Reliability

Content validity was assessed by a panel of five Information Systems academics and three Iraqi manufacturing practitioners. Construct validity was evaluated through the PLS-SEM measurement model using AVE > 0.50 and Composite Reliability > 0.70 as convergent validity thresholds (Hair et al., 2022). Discriminant validity was assessed using the HTMT criterion (threshold: 0.85; Henseler et al., 2015). Internal consistency was confirmed via Cronbach's Alpha ($\alpha > 0.70$; Taber, 2018).

3.5 Analytical Approach

PLS-SEM (Smart-PLS 4.0) was selected for three reasons: (1) the prediction-oriented model structure and mixed reflective-formative specification; (2) confirmed non-normality in key constructs (Kolmogorov-Smirnov tests), which violates CB-SEM distributional assumptions; and (3) PLS-SEM's distribution-free bootstrapping is well-suited to the moderate sample size. Analysis proceeded in two stages — measurement model evaluation (convergent and discriminant validity) followed by structural model testing (path coefficients, R^2, Q^2, f^2, VIF). Bootstrapping with 5,000 resamples generated t-statistics and 95% bias-corrected confidence intervals. PLS-predict was additionally employed to assess out-of-sample predictive accuracy (Q^2_predict), as recommended for prediction-oriented PLS models (Shmueli et al., 2019).

3.6 Common Method Bias

The inherent common method bias (CMB) was evaluated under the question of the single factor test, as well as the complete collinearity evaluation plan, proposed by Harman (Single Factor Test) and by Kock (2015). The biggest values of the inner VIF were less than 3.3, which means the acceptable level of CMB. Moreover, a variable marker strategy (Lindell and Whitney, 2001; Podsakoff et al., 2012) was used as a higher test of procedure; the adjustments were made to the observed correlations, but it did not have a significant effect on the pattern or significance of structural relations. Procedural controls were achieved by spacing out questionnaire sections, anonymity of the respondents and the use of reverse coded items.

4. Results

4.1 Sample Demographics

Demographic data of the 285 participating firms is summarized in Table 2. The stratified sample was representative of the registered firms for the Iraqi manufacturing sector in terms of sub-sector, size of the manufacturing plant and years of operation.

Table 2. Demographic Profile of Participating Manufacturing Firms (n = 285)

Characteristic	Category	Frequency	Percentage
Industry Sector	Food Processing	78	27.4%
	Textiles & Apparel	52	18.2%
	Metal Fabrication	48	16.8%
	Construction Materials	41	14.4%
	Chemicals	35	12.3%
	Other	31	10.9%
Firm Size	Small (10–49)	118	41.4%
	Medium (50–199)	127	44.6%
	Large (200+)	40	14.0%

Years in Operation	< 10 years	89	31.2%
	10–20 years	102	35.8%
	> 20 years	94	33.0%

4.2 Descriptive Statistics

Table 3 shows that the mean scores were for all study constructs in a positive direction with standard deviation between 0.15 and 0.39, indicating no major deviation from the norm values. The test of normality revealed that all constructs were normally distributed, and the values of skewness did not exceed the limit of 0.6. The highest means (M = 4.18) is obtained in the case of Perceived Relative Advantage, suggesting that the manufacturers tend to consider IT mostly at the level of productivity. The slightly non-normal data found in the IT Adoption Level subscale result (K-S p = 0.097) further supports the PLS-SEM estimator of the distribution free property.

Table 3. Descriptive Statistics for Technology Constructs and Outcome Variables

Construct / Item	Mean	SD	Min	Max	K-S p	Skewness
Technological Drivers (1=Not Important; 5=Very Important)						
Perceived Relative Advantage	4.18	0.92	1	5	0.094	−0.31
Technology Compatibility	3.95	0.98	1	5	0.108	−0.27
Technology Complexity (reversed)	3.62	1.03	1	5	0.121	0.19
IT Adoption Level	3.54	1.07	1	5	0.097	−0.22
Manufacturing Performance	3.71	0.94	1	5	0.083	−0.28

Note. K-S = Kolmogorov-Smirnov test. Technology Complexity is reported after reversal scoring; a higher score indicates greater perceived ease of use.

4.3 Measurement Model

Convergent validity and reliability indicators are shown in Table 4. Convergent validities and internal consistencies of all constructs conform to the major criterion, such as AVE values higher than 0.50, CR values higher than 0.70, and α values higher than 0.70.

Table 4. Convergent Validity and Reliability — Measurement Model

Construct	Cronbach's α	Composite Reliability	AVE	Min. Loading	Max. Loading
Perceived Relative Advantage	0.82	0.88	0.59	0.73	0.85
Technology Compatibility	0.79	0.85	0.55	0.71	0.83
Technology Complexity	0.77	0.84	0.53	0.70	0.82
IT Adoption Level	0.84	0.89	0.63	0.76	0.87
Manufacturing Performance	0.88	0.92	0.67	0.79	0.89

Table 5 presents the HTMT discriminant validity matrix. All inter-construct HTMT ratios fall below the 0.85 threshold (Henseler et al., 2015), confirming that each construct is empirically distinct from the others.

Table 5. Discriminant Validity: HTMT Matrix

Construct	1	2	3	4	5
1. Perceived Relative Advantage	—				
2. Technology Compatibility	0.54	—			
3. Technology Complexity	0.47	0.51	—		
4. IT Adoption Level	0.69	0.63	0.58	—	
5. Manufacturing Performance	0.61	0.57	0.52	0.74	—

Note. All HTMT ratios < 0.85, confirming discriminant validity. Diagonal entries are not applicable.

4.4 Structural Model and Hypothesis Testing

Path coefficients are standardized, as indicated in Table 6 where t and p values, bias corrected bootstrapped 95% confidence intervals, and Cohen's f^2 effect sizes are also provided. Inner VIFs values were below 3.3, which suggests no multicollinearity or common method bias was an explanation threat.

Table 6. Structural Model Results: Hypothesis Testing (PLS-SEM, n = 285)

H	Path	β	t-value	p-value	95% CI [LL, UL]	f²	Result
H1a	Relative Advantage → IT Adoption	0.38	6.71	<0.001	[0.27, 0.49]	0.24	✓
H1b	Compatibility → IT Adoption	0.29	5.14	<0.001	[0.18, 0.40]	0.15	✓
H1c	Complexity → IT Adoption	−0.21	3.88	<0.001	[−0.32, −0.10]	0.09	✓
H2	IT Adoption → Manufacturing Performance	0.45	8.91	<0.001	[0.35, 0.55]	0.34	✓
H3	Firm Size × IT Adoption → Performance	0.23	4.12	<0.001	[0.12, 0.34]	0.09	✓

H1 — Technology Characteristics and IT Adoption (Supported). Perceived Relative Advantage was the strongest correlate of IT adoption ($\beta = 0.38$), followed by Technology Compatibility ($\beta = 0.29$) and Technology Complexity ($\beta = -0.21$). Collectively, the three DOI attributes are associated with 46% of the variance in IT Adoption ($R^2 = 0.46$).

H2 — IT Adoption and Manufacturing Performance (Supported). IT Adoption Level is significantly and positively associated with Manufacturing Performance ($\beta = 0.45$, $R^2 = 0.52$, $f^2 = 0.34$ — a large effect). IT adoption-level variance is associated with 52% of the explained variance in performance outcomes.

H3 — Firm Size as Moderator (Supported). The firm size interaction term is significant ($\beta = 0.23$, $t = 4.12$, $p < 0.001$, $f^2 = 0.09$), indicating that larger firms exhibit a stronger positive association between IT adoption and manufacturing performance. Firm size was dummy-coded (Small = 0, Medium = 1, Large = 2) and entered as a product-indicator interaction term in Smart-PLS 4.0.

4.5 Model Fit Indices

Model fit and predictive accuracy indices are listed in Table 7. These endogenously constructed items show positive Q^2 indicating predictive relevance. The SRMR value of 0.061 is within acceptable limit (< 0.08).

Table 7. Model Fit and Predictive Accuracy Indices

Index	IT Adoption Level	Manufacturing Performance	Criterion
R^2 (Coefficient of Determination)	0.46	0.52	—
Q^2 (Stone-Geisser)	0.27	0.34	> 0 = predictive

SRMR	0.061	—	< 0.08 = good fit
Max. Inner VIF	2.31	2.64	< 3.3 = no CMB
GOF (Global Goodness of Fit)	0.57	—	> 0.36 = large

Note. Q^2 calculated via blindfolding (omission distance = 7). SRMR based on the saturated model. CMB = Common Method Bias.

4.6 Sector-Level Comparative Analysis

A one-way ANOVA with Tukey post-hoc tests revealed significant differences in IT adoption levels across industry sub-sectors ($F(5, 279) = 15.67$, $p < 0.001$, $\eta^2 = 0.22$, large effect). Metal fabrication and chemicals firms exhibited the highest means of adoption, while construction materials and other sub-sectors lagged. Chi-square analysis confirmed significant sector-level variation in ERP penetration rates ($\chi^2 = 23.45$, df = 5, $p < 0.001$).

Table 8. IT Adoption Levels and ERP Penetration by Industry Sector

Industry Sector	n	Mean IT Adoption	SD	ERP Adoption (%)	Tukey Group
Metal Fabrication	48	3.84	0.92	67%	A
Chemicals	35	3.72	0.88	54%	A
Food Processing	78	3.45	1.05	41%	B
Textiles & Apparel	52	3.38	0.98	38%	B
Construction Materials	41	3.12	1.12	23%	C
Other	31	3.08	1.18	21%	C

5. Discussion

5.1 Technology Characteristics as Adoption Correlates

The support for all three DOI attributes results in congruence in H1 with both Rogers (2003) and Singh & Garg (2021) that substantiates the power of the DOI framework in post-conflict manufacturing situations. So the hierarchy Perceived Relative Advantage > Compatibility > Complexity is similar to that of other studies which explored the developing economy (Zhou & Zheng, 2023; Vu & Nguyen, 2022) and indicates that Iraqi managers consider IT primarily from an efficiency perspective, which is logic given the fact that there is significant potential for improving the productivity level in this environment. The negative sign for Technology Complexity ($\beta = -0.21$) agrees with Moeuf et al. (2020) and highlights the human-capital limiting factor prevailing in post-conflict labour markets. The acute technology-skills gap is present before face of Iraqi manufacturing SMEs (41% of sample) exacerbates the inhibiting effect of perceived complexity. The positive relationship of Technology Compatibility (β = 0.29) supports the idea that compatibility is a risk-reduction option in technology adoption decision.

5.2 IT Adoption and Manufacturing Performance

H2 is strongly supported (β = 0.45, $R^2 = 0.52$, $f^2 = 0.34$). This large effect size, which is comparable or even larger than reported in similar IT investments in manufacturing in other developing economies, is in line with the assumptions that returns can be relatively higher in post-conflict countries, where the baseline pre-adoption performance is lower. The pattern confirms Dalenogare et al. (2018) and Zheng et al. (2021) who proposed that any first-order productivity changes precede transformational effects of innovations. The benefits of the first-order innovation seem to be being by the Iraqi manufacturing firms, while the benefits of higher-order innovation products depend upon the rate at which the innovation is being adopted.

5.3 The Moderating Role of Firm Size

A significant positive moderation by the size of firms (β = 0.23, $p < 0.001$) is consistent with the predictions of RBV (Wernerfelt, 1984; Li et al., 2022): larger firms have the complementary resources (stable IT infrastructure, educated human capital, and organizational learning capacity) to facilitate the transformation of IT into long-term performance improvements. As is evident, they have direct policy implications such that the symmetrical approach of implementing uniform adoption-support programming will systematically under-serv a vast majority of firms, these being the small and medium enterprises. To obtain this equalization of IT performance returns across the firm-size distribution, a series of differentiated support mechanisms (e.g., user-friendly interfaces where appropriate, infrastructure-specific IT training, and simplified IT purchasing systems) is needed.

5.4 Theoretical Contributions

This research has three theoretical contributions. Firstly, it has generated reproducible effect size benchmarks (R^2 IT Adoption = 0.46; R^2 Manufacturing Performance = 0.52) for the comparison of future post conflict research for IT adoption and manufacturing performance in Iraq. Secondly, it is the first validated model of IT adoption for Iraqi manufacturing using PLS-SEM focusing on the technology characteristics of the product. Second, the study shows that a parsimonious three-predictor DOI model performs better in explaining technology adoption than most multi-dimensional TOE models do in similar studies (Nekmahmud & Fekete-Farkas, 2023), further supporting theoretical parsimony in technology adoption studies. Third, DOI and RBV are integrated into one validated model which has a firm size as a theoretically grounded moderator, which meets the theoretical integration agenda set out by Awa et al. (2017).

6. Conclusion and Implications

6.1 Theoretical Implications

This research adds to the existing body of work on IT adoption in post conflict manufacturing economies (PMAEs) by showing how an IT characteristic/ DOI model with only few factors is enough to account for meaningful variation in both IT adoption ($R^2 = 0.46$) and manufacturing performance ($R^2 = 0.52$). Model generates clean, replicable levels of effect-size benchmarks for latter-day cross country comparative research (such as Iraq, Libya, Syria) and offers analytically parsimonious alternative to multi-dimensional models.

6.2 Practical Implications

Finally, the positive association of Perceived Relative Advantage (β = 0.38) with the adoption of IT deserves a communications strategy that focuses on concrete and sector-specific productivity proof, as opposed to tales of digital transformation. The development of measures that directly target identifiable and sector-specific efficiency gains in technology should be the focus of Iraqi industrial policy and associations. The negative correlation of Technology Complexity (0.21) reinforces the need for investment in low complexity IT solutions that are user-friendly and focus on resource-constrained SMEs. Interface simplicity shouldn't be a key assessment factor in public procurement and international development IT projects in Iraq. The positive moderation by firm size ($\beta = 0.23$) supports the notion that a generic or undifferentiated approach to incentivizing IT adoption will have a greater positive impact on larger firms. Policy instruments need to be tailored to level the IT performance returns to the entire distribution of firm-size.

6.3 Limitations

Four limitations merit acknowledgement. The cross-sectional design prevents a causal interpretation; longitudinal panel data would provide more powerful directional inferences and allow for tracking over time of the adopters' trajectories. Second, while procedural controls were implemented to reduce CMB when assessing self-reported performance measures in this study, future research can complement these findings with examination of objective administrative performance records which are less susceptible to social desirability bias. Third, the sampling frame from which we recruit registered firms systematically omits the informal manufacturing sector—likely, a substantial fraction of Iraqi industrial activity—which may restrict generalizability. Fourth, the geographic concentration in Baghdad (34.4%) and Basra (23.5%) make these findings less representative of peripheral governorates in Iraq.

6.4 Future Research Directions

Longitudinal panel designs capturing longer term performance effects in the anti-corruption context of post-reconstruction Iraqi manufacturing are recommended for future studies. Furthermore, cross-country comparative studies using PLS-SEM methodology would help validate whether the technology characteristics effects found by DOI Theory are consistent in other emerging post-conflict economies (like Libya and Syria), thus improving generalizability of findings. Additionally, future research might improve upon the model proposed by integrating elements of Industry 4.0 into the existing DOI-RBV framework, which would help provide insight on how trends in technology affect approach to adoption and performance characteristics within organizations. Finally, the consideration of organizational capabilities, particularly IT absorptive capacity and managerial IT knowledge, as potential mediators between IT adoption in manufacturing and performance provides an important avenue for future research because this analysis may improve our understanding of how technology adoption opportunity translates into objective performance improvements.

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