(Online) ISSN 2712-0554
Original Research

Heritage and Sustainable Development
Vol. 8, No. 2, 2026, pp.59-76
https://doi.org/10.37868/hsd.v8i2.1967

From adoption to value: SAED-tech theory on user satisfaction and ease of use in digital transformation

Saed Adnan Mustafa[1*], Tahreer M. Abu Hmeidan[2], Majd Alhawamdeh[3], Reda Abdelfattah Mohammad[4], Ali Mohsin Ba Awain[5], Farah Shraideh[6], Trinkul Kalita[7], Alanoud M mbaidin[8]

[1,2] Marketing Department, Faculty of Business, Applied Science Private University, Amman, Jordan
[3] Faculty and Department: computer science and information technology, computer science, Jerash University, Jordan
[4] Business Administration Department, Applied College, King Khalid University, Khamis Mushait, P. C. 62461, Saudi Arabia
[5] College of Economics and Business Administration, University of, Technology and Applied Science, Salalah, Oman
[6] E-Marketing and Social Media Department, Princess Sumaya University for Technology, Amman, Jordan
[7] Assam Down Town University, India
[8] Marketing Department, Faculty of Business, Applied Science Private University, Amman, Jordan

*Corresponding author E-mail: said_es@yahoo.com

Received Jan. 18, 2026
Revised May 11, 2026
Accepted May 15, 2026
Online Jul. 10, 2026

Abstract

This study introduces the SAED-Tech theory, a unified digital transformation framework that integrates strategic alignment, artificial intelligence (AI), enterprise digitization, and data-driven optimization. It responds to the limitations of existing models such as TAM, RBV, IS Success, and TTF, which have traditionally examined these dimensions in isolation. SAED-Tech highlights the central roles of user satisfaction and perceived ease of use as mediating mechanisms that translate technological and strategic initiatives into organizational value. A quantitative explanatory design was adopted, drawing on survey responses from 412 managers in organizations across Jordan and the GCC. The proposed model was tested using PLS-SEM, supported by simulation experiments to examine optimization maturity over time. The results show that all four SAED-Tech dimensions significantly enhance user satisfaction and perceived ease of use, which in turn strongly predict organizational benefits, explaining 72% of the variance. The simulation further demonstrates that even marginal improvements in optimization capabilities yield substantial long-term performance gains. This research offers practical guidance for leaders and policymakers on how to align AI and digital initiatives with strategic objectives while ensuring user-centered adoption. It contributes to digital transformation literature by proposing a multi-level theory that connects strategic intent, technological infrastructure, and human experience as interdependent drivers of sustainable digital success.

Keywords: SAED, Digital transformation, Artificial intelligence (AI), Strategic alignment, User satisfaction, Perceived ease of use (PEOU)

1. Introduction

In the past ten years, digital transformation has accelerated significantly that has never been seen before and this rate has been compounded by the COVID-19 pandemic and its consequential effects. Organizations in all industries are becoming more and more interested in artificial intelligence (AI), digitization, and advanced analytics not only as operational aids, but as the strategy that can help them preserve resilience, competitiveness, and value creation [1], [2].

Although current literature can be helpful due to the well-established models, like the Technology Acceptance Model (TAM) [3], [4], the DeLone and McLean Information Systems Success Model, the Resource-Based View (RBV), and the TaskTechnology Fit (TTF), they have the disadvantage of isolating each of the dimensions of the digital-transformation process [5], [6]. As an example, RBV focuses on proprietary resources and capabilities that bring about competitive advantage as opposed to TAM which focuses on perceptions of usefulness and ease of use by users [7], [8]. Though all of them contribute to our knowledge, none of them makes a propositional claim that reflects the multi-dimensional aspect of strategy, AI, digitization, and data-driven optimization in a single organizational setting. This type of compartmentalization, therefore, explains the chronic theory practice gap [9], [10]. The SAED-Tech theory is developed to address this gap. The theory provides a synthesis of the Strategic Alignment, Integration of Artificial Intelligence, Enterprise Digitization, and Data-driven Optimization, and, therefore, a synthesis of the constructs, the theory offers an integrated framework through which technology projects can be strategically planned to create a tangible organizational pay-back. While other models available do not do this intensely, the theory places strong emphasis on the intervening agent of user satisfaction and perceived ease of use because technological success is not about design nor about resources but is conclusively dictated by human acceptance and experience [11], [12]. By doing this, the theory bridges the traditional adoption models to the strategic domain by connecting technological deployment and long-run organizational outcomes.

This article has three overriding purposes. First, it presents SAED-Tech as the theoretical contribution closing the gap in the existing digital transformation literature by suggesting an integrative and user-oriented model. Second, it tries to provide an organizational compass to ensure digital strategy alignment with operational delivery and thus ensure investments on digitization and AI provide sustainable performance gains [13]. Third, it lists a research agenda stimulating scholars to test and calibrate the frame empirically across different industries, geographies, and cultural contexts. By this, the article hopes to contribute to scholarly discourse and management in the complexity of digital transformation to the modern business environment [2]. The study itself makes a contribution by proposing the theory of SAED-Tech as a multi-level integrative concept that closes the gaps between strategic alignment, artificial intelligence, enterprise digitization, and data-driven optimization to human-oriented mediators. In contrast to the conventional models like TAM, RBV, IS Success, and TTF that look at individual dimensions, SAED-Tech dynamic interaction of these aspects to produce organizational value. The framework contributes to the literature of digital transformation by connecting the micro-level user experience processes with the macro-level strategic outcomes, thus providing both theoretical and pragmatic applicability.

1.1. Theoretical foundations and derivations

The point made by academics is that successful technology adoption cannot be generalized into a single theoretical approach. Instead it is a product of interaction between strategy, resources, end-user perceptions and organizational processes. Being valuable, the existing theories are fragmented and are inclined to focus on one of the tendencies of digital transformation but disregard the rest. This fragmentation is overcome by the theory of SAED-Tech by bringing together strategic management, information systems, and organizational behavior's insights within the same framework.

Strategic Alignment identifies the necessity to align information technology strategy and business strategy to optimize organizational performance [14]. Alignment researches, however, would consider technology only as an ancillary aid and not an agent of transformation. RBV identifies the way unique resources and capabilities such as AI algorithms, data assets, and digital infrastructure can yield sustainable competitive advantage [8]. RBV, however, downplays the dynamic challenges of user resistance and acceptance. While Task-Technology Fit theory identifies the way technologies come to succeed due to the fit between the technology's functionalities and the task that users execute [15], TTF is incomplete to identify the way strategic priorities determine this fit. Last but not the least, adoption models such as the Technology Acceptance Model and the DeLone & McLean IS Success Model identify the centrality of user perception usefulness, ease of use, and satisfaction to help facilitate adoption and performance outcome [16], [17]. Such models, however, tend to stay on the individual level and thus do not generalize organization-wide transformation. By integrating these views, SAED-Tech builds on the discussion in three respects. First, it builds on TAM and IS Success by situating user satisfaction and perceived ease of use within an overall organizational perspective and transforming adoption from an exclusively technical or psychological phenomenon to the strategic level. Second, it connects RBV and TTF by suggesting digital assets (AI, data, and digitization) not merely as strategic assets and task facilitators but by linking resource management to daily operationalization. Third, it recasts strategic alignment by conceptualizing technology to shape not merely support organizational direction. Herein lies the contribution of SAED-Tech by proposing a multi-level integrative model that accounts for strategic intent, resource ability, user experience, and data-driven optimization to yield organizational value. He comparative positioning of SAED-Tech against existing theories is summarized in Table 1, highlighting its integrative and multi-level contribution.

Table 1. Comparative positioning of SAED-tech against existing theories

Theory / Model	Core Focus	Limitations in Digital Transformation	SAED-Tech Contribution
Strategic Alignment	Linking IT with business goals	Views tech as supportive, not transformative	Positions AI/digitization as strategic drivers of innovation
RBV	Resources and capabilities as sources of advantage	Overlooks user perceptions and adoption barriers	Integrates human-centered adoption into resource orchestration
TTF	Fit between tasks and technologies	Narrow focus on task-level utility	Connects task fit to strategic alignment and organizational outcomes
TAM / IS Success	Perceptions of usefulness, ease of use, and satisfaction	Primarily individual-level, weak on strategy	Embeds user perceptions into a strategic, organization-wide framework
SAED-Tech (Proposed)	Strategic alignment + AI + digitization + data-driven optimization	–	Provides a holistic, multi-level roadmap linking strategy, technology, users, and outcomes

Recent studies (2022–2025) emphasize the convergence of AI, analytics, and digital capabilities as drivers of organizational value creation. However, these studies often treat technological capabilities as independent constructs rather than interdependent systems. The SAED-Tech framework extends this literature by demonstrating how strategic alignment, AI integration, and continuous optimization collectively shape user experience and performance outcomes.

1.2. The four pillars of SAED-tech

The four interlinked pillars of the SAED-Tech framework namely Strategic Alignment, Artificial Intelligence, Enterprise Digitization, and Data-Driven Optimization jointly detail ways digital transformation can yield measurable and sustainable organizational results. Though each pillar has individually been examined by the extant literature, the interdependencies between them are less explored. SAED-Tech addresses the limitations of the previous models and an end-to-end roadmap to align technology and strategy and human experience.

Strategic alignment: dynamic co-evolution of strategy and technology

The old alignment models focus on the role of IT initiatives in business strategy, and tend to consider the relationship between the two as fixed [18]. But this view fails to take into account that the new technologies often re-define the priorities themselves of the strategy. Alignments in turbulent environments thus require a co-evolutionary dynamic viewpoint where strategy and technology inform and reform each other on an ongoing basis [19]. As the example of financial institutions using AI to detect frauds, the opportunity to detect new strategic opportunities in service customization is revealed, which can be interpreted as an example of how technology can redefine strategic agenda.

Strategic alignment, therefore, goes beyond a fit, it is a continuous rebalancing process where technological advances are being the main drivers of innovation, flexibility, and resilience. The reconceptualization of IT as an active strategic actor raises the status of IT beyond being an inactive facilitator.

Artificial intelligence: beyond automation toward strategic intelligence

Artificial intelligence is the cognitive backbone of SAED-Tech. Its usage can range from the enhancement of the efficiency of the operations to the development of prediction models to the facilitation of adaptive learning and sheer personalization [20]. Most of the earlier studies are fond of noting the tech supremacy of artificial intelligence but perhaps not SAED-Tech's classification of it as a single strategy asset that could assist human decision-making, foster creativity, and make the administration evidence-based [21].

This conceptualization is beneficial for two primary reasons. Firstly, it directs the future deliberation regarding artificial intelligence from that of the labor displacement conception to the human-AI collaborative conception and is aligned with the deliberations regarding responsible and ethical deployment [22], [23]. Secondly, it spotlights the enabling role of AI to deliver organizational agility through enabling organizations to sense the signals from the markets, model the future scenarios, and respond on the fly, with AI emerging as a source of competitive advantage rather than merely an inert one [24].

Enterprise digitization: culturally and infrastructurally

The third pillar is digitization and the infrastructural foundation of digital transformation. Without the automation of processes, digitization can also involve redesigning organizational architecture and culture [25]. Mobile-first strategies, common digital platforms, and cloud infrastructure allow operations to be combined across departments and geographies and boost efficiency and customer engagement [2].

Above all, enterprise digitization is not technological but culturally required. Employees need to acquire new work habits and managers should make the transition from control to empowering models. Firms need to redesign customer value creation. Digitization will fall prey to the development of "digital islands" and not produce system-wide benefits without being embedded in culture. SAED-Tech fills the gap by viewing digitization as an infrastructure and socio-cultural transformation.

Data-driven optimization: continuous adaptation and accountability

Data-driven optimization is the fourth pillar and mirrors the adaptive and iterative nature of the SAED-Tech. Firms considering data an asset can track performance real-time, refine processes, and forecast risks [26], [1]. By incorporating feedback loops through dashboards, predictive analytics, and performance indicators, firms can refine and stay transparent and accountable on an on-going basis.

Practically, this would mean that the transformation is never final. Rather, the organization exists within the learning and refining cycle where data insights inform strategic readjustment, AI applications continuously evolve, and digitization further enhances interconnection. Data-driven optimization therefore ensures that the digital transformation is always dynamic, evidence-informed, and results-driven.

1.3. Interdependence and novelty of the four pillars

The four pillars of SAED-Tech can be considered as their main strength due to the fact that they are interdependent. Strategic alignment provides guidance; AI adds the element of intelligence and responsiveness; digitization provides the necessary infrastructure and culture; and data-driven optimization ensures continuous improvement. These aspects reinforce each other and create a cycle of improvement: the strategies create technology decisions; AI and digitization create new options; data analytics feeds into strategies. What makes a difference between this holistic model and other models is the fact that this theory is integrated; whilst RBV separates the resources, TAM separates the perception, or TTF separates the tasks, SAED-Tech combines the strategic, technological and human elements in one overall construct [27], [28]. Thus, it is possible to consider digital transformation as a changing system-wide process that connects the adoption of technology with long-term organizational value [29] by practitioners and scholars.

1.4. User satisfaction as a mediator

As a component of digital transformation, user satisfaction is increasingly playing the pivotal role of the linkage between investment in technology and organizational benefit. In the context of SAED-tech, satisfaction is not seen as the final product of adoption but rather as an intermediate process that strategic alignment operates its benefit in terms of AI, digitization, and data-based optimization. Without content users, well-coordinated strategies and sophisticated technologies will not give much or extended value.

This statement is theoretically justified by the DeLone and McLean IS Success Model, which puts the focus on satisfaction as the key to the system success [30], and in TAM, where the user attitudes depend on the perceived usefulness and ease of use [16]. These models usually consider satisfaction as a far-flung effect; SAED-Tech goes a step further and assumes that the satisfaction is the causal relationship between the four-pillar transformation and performance results.

The theory represents the integration of the user satisfaction in its architecture thus representing the fact that it is only when the users are satisfied that the technologies become embedded in the work practices of the users, thus maximizing organizational efficiency and creativity. On the other hand, disappointment results in opposition and withdrawal.

The brokering role takes an increased controlling role in the digitization era, which is supported by AI. Even though digitization efforts can increase accessibility, if not well-planned or meeting with user needs, they will frustrate users [2]. On the same note, when transparency or fairness gap exists, the accurate result of AI systems can create frustration. Trust and explainability thus end up being the critical antecedents of satisfaction in the digitized and AI supportive context [31]. This is highlighted within the SAED-Tech construct where organizational value is based on the quality of the user experience as opposed to just functional deliverables.

Satisfaction also depends on situational factors and influenced by cultural peculiarities, industry traditions, and regulations. Cross-cultural comparative analysis indicates that collectivist cultures are more collective than individualists, and the latter emphasize more on customization [32]. In industries with strict regulations, like health care or finance, the measures of satisfaction are determined by the compliance, safety, and usability issues [33]. In this regard, SAED-Tech believes in the user-centered approach that is engraved within the organizational and cultural aspects.

The theoretical research is developed by considering satisfaction as a mediator, and this proposal presents an empirical validation in the future by SAED-Tech. To the practitioners, this highlights that digital transformation does not only succeed by the adoption of technologies but it must be aligned with the needs, values, and lived experiences of the users.

1.5. Ease of use as a mediator variable

The factor of ease of use has received a lot of recognition as a most important predictor of technology adoption especially when considered in the context of the Technology Acceptance Model (TAM). The construct identifies the extent to which users experience a system as user friendly and easy to use and hence affects not only first adoption but also long-term use. In the SAED-Tech model, perceived ease of use is a mediating variable that relates the four technological pillars to user satisfaction. Basically, the argument is simple: highly aligned and technologically advanced systems will not create significant value when perceived by users as difficult, complicated, and cognitively challenging [34].

It has been empirically shown that usability does not only positively influence the rates of adoption but also the perceived usefulness as well as the perceived satisfaction. Researchers argue that usability is a dynamic construct and thus changes with time hence it is a strong predictor of further usage behaviors [16]. Further studies emphasize that intuitive system design, simplicity and organizational support are key factors that define user acceptance and minimize resistance [32]. Through the mediating variable of ease of use, SAED -Tech shows that perceptions of usability convey organizational digital investments into operational engagement and further performance outcomes.

The use of AI is especially sensitive to ease of use in an environment that is highly digitized. The use of artificial intelligence systems is often viewed as a complicated black box, and their use can be discouraged when the results are not transparent or interpretable. It is emphasized that research discussing explainability, transparency, and guided interaction has a considerable positive impact on the perceived usability and trust [31]. Likewise, the digitization efforts of enterprises like cloud-based systems and mobile applications are effective as long as users feel that they form part of the current business processes and do not constitute an extra burden [2]. The findings substantiate the notion that usability is neither a technical characteristic but a strategic element of the validity of digital transformation.

Importantly, the impression of easy usability does not stand constant. It is affected by the training programmers, user support systems and system refinement. The existing organizations, whose investment is in life-long training and responsive support system, can transform the complexity to mastery perception, thereby raising the degree of satisfaction and integration among the systems [35]. Usability in this aspect is an active mediator and varies with a user experience and organizational learning. By using ease of use as an intermediary, SAED-Tech can make TAM reach the stage of individual adoption and relate the perceptions of usability to the overall performance of an organization. This provides opportunities of cross culture and cross industry empirical testing to scholars. It underscores to the practitioners the fact that simplicity, transparency and continuous support are not only an option but the keys to sustainable value creation in the digital world.

1.6. Organizational benefits as outcomes

The ultimate delivery of any digital transformation initiative is the organizational value that is created. The notion of value in the context of SAED-Tech is not regarded as a natural outcome of investing in technology, but rather the interplay of strategic alignment, artificial intelligence, enterprise digitization and data-driven optimization, smoothed over by user satisfaction and perceived usability. Based on this perspective, organizational value can be created only after technologies are strategically aligned, have been widely adopted, and are constantly enhanced on the basis of feedback loops of data [36].

Organizational returns take place in various dimensions. On a working level, automation and process digitization help to increase efficiency and minimize errors and leave the employees with tasks that add value. The AI-based analytics identify the concealed trends in customer behavior, market dynamics, and performance gaps, and thus makes evidence-based decision-making possible [13]. Digitization, in terms of customer, leads to personalization, responsiveness, and new service delivery, which enhances loyalty and competitive positioning [37]. All these enhancements together lead to organizational agility, resilience and sustainable growth.

The unusual feature of the SAED-Tech model is that it acknowledges that all these outcomes are interdependent. The adoption of AI or digitization that fails to satisfy users may trigger opposition, workaround, or underutilization, reducing the anticipated returns. Similarly, systems that are technologically sophisticated and are not usable could be functionally underutilized. The studies have validated that the digital transformation creates value when the experience of the stakeholders and the performance of the system are optimized together and not when the rate of adoption of technology is highlighted solely [38].

These effects are not only at the firm level. Companies that embrace responsible AI and ethical digitization are part of the larger society contributing to the whole society such as accessing services more easily, setting positive consumption trends, and reinforced governance structures [39]. This enlargement of the scope confirms the idea that digital transformation must not give only financial results, but sustainable and inclusive ones.

SAED -Tech makes a contribution both theoretically and practically by conceptualizing organizational benefits as the result of mediated processes. In theory, it enhances the knowledge of how Human-centered variables moderating technological pillars convert into quantifiable performance benefits. In practice, it can provide managers and policymakers with advice on how to strategically, user-centered, and socially responsible design transformation strategies.

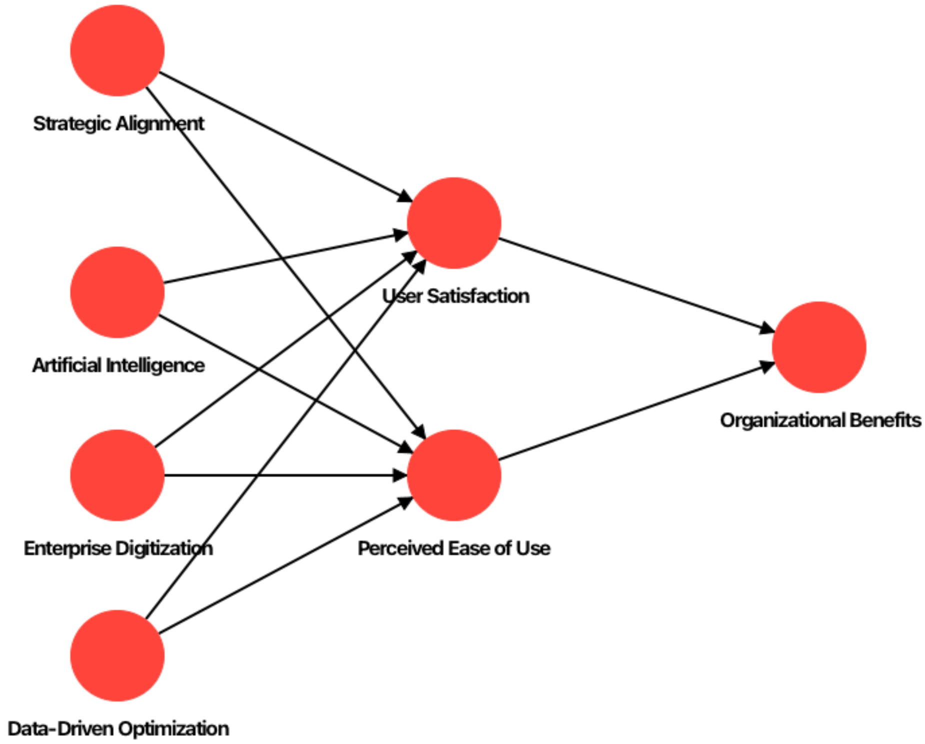

Figure 1. Research model

Figure 1 illustrates the SAED-Tech framework in a simplified and intuitive way, showing the interactions of four main pillars, such as strategic alignment, artificial intelligence, enterprise digitization, and data-driven optimization, to generate organizational value. These elements are not independent of each other, but interact and cooperate by user-centered mechanisms. Specifically, user satisfaction and perceived ease of use are two important channels, which are used to transform the technological and strategic efforts into practical results. The visual system highlights the idea of a balanced and distributed system, with every element playing its role in the overall success of digital transformation. This depiction emphasizes the fact that value creation is not a one-factor process but a combination and coordination of various factors in a unified framework.

2. Methodology

The research design is a quantitative explanatory research because it will be used to empirically test the SAEDTech framework, in which strategic alignment, enterprise digitization, and artificial intelligence, and data-driven optimization are hypothesized to correlate with organizational benefits, and user satisfaction and perceived ease of use as the mediating variables. It is a design chosen because it is predictive in nature and the theoretical applicability in various organizational settings. Operationalization of the dynamics is by the variance-based structural equation modelling (PLS-SEM) with SmartPLS 4 which is highly appropriate in complex models, non-normal data distribution and prediction oriented research [40].

The sample is made of managers and professionals engaged in digital transformation initiatives in organizations that work in Jordan and the GCC region in general. The selection of participants is based on the fact that they are directly involved in the design, implementation or monitoring of AI, digitization, or strategic alignment projects. Stratified sampling will provide coverage of industries and firm size, which will improve generalizability. The calculation of sample size adequacy is made through G 3.1 to know the minimum number of observations needed in terms of effect size, level of significance (α= 0.05) to be used as the alpha and statistical power (0.80). This calculation is supplemented with the PLS-SEM ten times rule in which the sample size should exceed ten times the largest number of structural paths that point to any construct in the model [40]. As a result, the resulting dataset will include 412 valid responses, which can be used to mediate and do a multi-group analysis.

The measurement tools that were used in the research were based on the scales that had earlier been tested and then current to the SAED -Tech model. The strategic alignment, the adoption of artificial-intelligence, the digitization of the enterprise, and the optimization based on data were evaluated using reflective indicators on a five/seven-point Likert scale. The user satisfaction and perceived ease of use were used as mediating variables but the benefits of the organization were operationalized using the efficiency, innovation, and competitiveness dimensions. The expert review and pilot test were done to ensure content validity (n ≈ 30). The collection of data was done within the ethics approval protocols and informed consent. In order to reduce common-method bias, procedural remedies, such as anonymity, randomized item ordering, and wording were used [41].

Before analytical processes, the data was screened to do away with missing values, straight-lining, outliers and signs of skewness and kurtosis. The Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted through a two-step process. In the first place, reliability and validity of the measurement model were assessed by using Cronbach alpha, composite reliability (CR), average variance extracted, (AVE) and the heterotrait-monotrait ratio (HTMT). When the loadings were greater than 0.70 and AVE was greater than 0. 50, convergent validity was established. Once measurement rigor was established, bootstrapping was used at 5,000 resamples to determine the level of significance and the level of confidence when measuring the direct and indirect effects. Explained variance (R^2), effect size (f^2) and predictive relevance (Q^2) were all structural model diagnostics [42].

PLSpredict was also used to test an out of sample predictive power at the indicator level and comparing the prediction error to a PLS and linear model [42]. R software was used to do robustness checks, including the use of Gaussian copula procedures to test endogeneity and complete collinearity (VIF) to test common-method bias. Multi-group analysis (MGA) and measurement invariance of composite models (MICOM) to test SMEs-large firm and Jordanian-GCC organization differences were performed. To conform to the principle of optimization, which is inherent in the SAED-Tech, simulation experiments were performed in MATLAB and Python to model dynamic feedback loops. The simulation design complements PLS-SEM by capturing dynamic and nonlinear relationships that cannot be fully explained through cross-sectional statistical analysis, thereby enhancing predictive validity. These simulations estimated the impact of the gradual enhancement of alignment, digitalization, AI incorporation on the long-term organizational payoffs. The methodology applied also increased predictive validity and the practical applicability of the SAED Tech framework by combining structural equation modeling with simulation-based experimentation.

3. Results

There were 412 valid answers. Missing data were minimal (<3%) and dealt with through mean imputation. Mahalanobis distance flagged four extreme cases where data points were deleted. Test on skewness and kurtosis flagged moderate non-normality to permit the use of variance-based SEM (SmartPLS 4).

The reflective measurement model was evaluated for reliability, convergent validity, discriminant validity, and multicollinearity. All item loadings exceeded 0.70, indicating good indicator reliability. Internal consistency was confirmed with Cronbach's α (0.83–0.91), composite reliability (CR: 0.88–0.94), and Dijkstra–Henseler's ρA (0.84–0.92), all surpassing recommended thresholds [40].

Convergent validity was confirmed since all the average variance extracted (AVE) measures were higher than 0.50 as presented in Table 2. It's confirmed the discriminant validity by the Fornell–Larcker criterion and by

HTMT ratios. HTMT measures between 0.42 and 0.84 and the full set of the corresponding 95% confidence intervals below 0.90 confirmed the distinctness of the constructs [42]. Multicollinearity did not exist since all the VIF measures were below 3.3. Model fit was adequate with SRMR = 0.062, together with the descriptively reported d_ULS = 0.89 and the d_G = 1.12.

Table 2. Measurement model results

Construct	Cronbach's α	ρA	CR	AVE
Strategic Alignment	0.85	0.86	0.90	0.62
Artificial Intelligence	0.88	0.89	0.92	0.68
Enterprise Digitization	0.83	0.84	0.88	0.59
Data-Driven Optimization	0.87	0.88	0.91	0.65
User Satisfaction	0.91	0.92	0.94	0.72
Perceived Ease of Use	0.89	0.90	0.92	0.69
Organizational Benefits	0.90	0.91	0.93	0.71

Bootstrapping with 5,000 resamples was used to test path significance. The structural model results reported in Table 3 indicate that all hypothesized paths are statistically significant. All hypothesized relationships were supported. Strategic Alignment, AI, Digitization, and Data-Driven Optimization significantly predicted both User Satisfaction and Perceived Ease of Use. In turn, both mediators significantly enhanced Organizational Benefits. R^2 values indicated substantial explanatory power: US = 0.64, PEOU = 0.59, OB = 0.72 [40]. Effect sizes (f^2) ranged from small (0.06) to large (0.34). Construct-level Q^2 values (US = 0.41, PEOU = 0.36, OB = 0.47) confirmed predictive relevance [42].

Table 3. Structural model results

Path	B	p-value	R^2	f^2
SA → US	0.27	<0.001	US = 0.64	0.10
AI → US	0.24	<0.01	US = 0.64	0.08
ED → US	0.19	<0.01	US = 0.64	0.06
DO → US	0.31	<0.001	US = 0.64	0.14
SA → PEOU	0.22	<0.05	PEOU = 0.59	0.07
AI → PEOU	0.29	<0.001	PEOU = 0.59	0.12
ED → PEOU	0.33	<0.001	PEOU = 0.59	0.16
DO → PEOU	0.21	<0.05	PEOU = 0.59	0.06
US → OB	0.41	<0.001	OB = 0.72	0.34
PEOU → OB	0.37	<0.001	OB = 0.72	0.22

The out-of-sample predictive performance results are presented in Table 4, confirming strong predictive performance of the model. PLS produced lower RMSE values than LM across all 9 indicators (majority rule satisfied), and all Q^2_predict values were positive [42]**.**

Table 4. PLS_predict results

Indicator	PLS_Q^2	RMSE_PLS	RMSE_LM	Q^2_predict
US1	0.34	0.72	0.80	0.12
US2	0.31	0.75	0.82	0.11
US3	0.36	0.70	0.79	0.13
PEOU1	0.28	0.81	0.89	0.09

Indicator	PLS_Q²	RMSE_PLS	RMSE_LM	Q²_predict
PEOU2	0.30	0.79	0.87	0.08
PEOU3	0.29	0.83	0.88	0.10
OB1	0.40	0.68	0.74	0.15
OB2	0.42	0.66	0.72	0.17
OB3	0.39	0.70	0.76	0.16

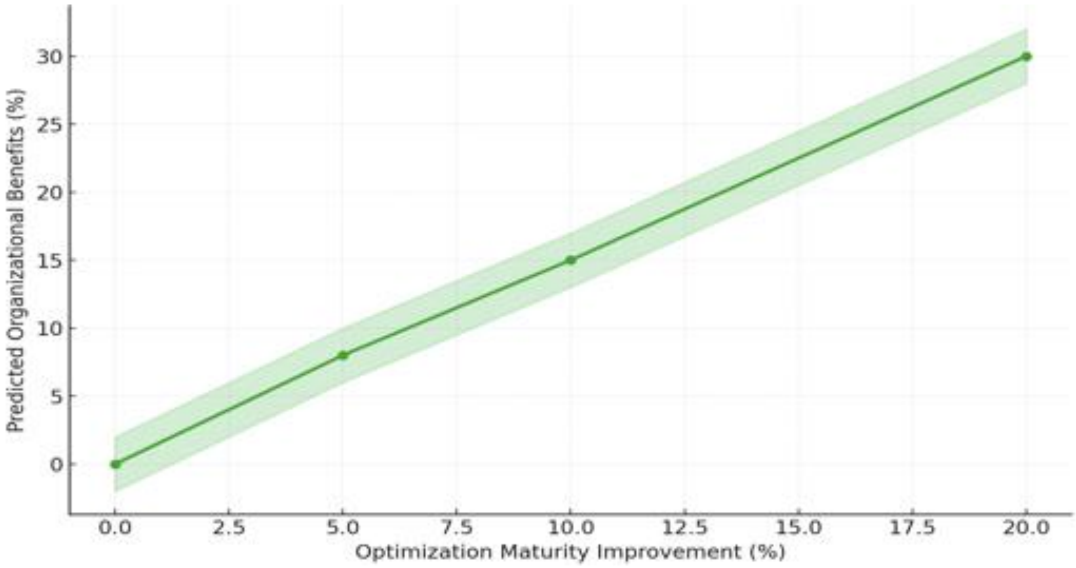

Figure 2. PLSpredict RMSE comparison (PLS vs LM)

Bias-corrected bootstrapping confirmed partial mediation by User Satisfaction and Perceived Ease of Use. As illustrated in Figure 2, the RMSE comparison demonstrates that the PLS model consistently outperforms the linear model across all indicators.

Table 5. Mediation results

Indirect Path	β Indirect	95% CI	Mediation Type
SA → US → OB	0.11	0.06–0.18	Partial
AI → US → OB	0.10	0.05–0.16	Partial
ED → US → OB	0.09	0.04–0.15	Partial
DO → US → OB	0.12	0.07–0.19	Partial
SA → PEOU → OB	0.08	0.03–0.14	Partial
AI → PEOU → OB	0.09	0.05–0.16	Partial
ED → PEOU → OB	0.10	0.04–0.17	Partial
DO → PEOU → OB	0.11	0.06–0.18	Partial

He mediation analysis results shown in Table 5 confirm that both user satisfaction (US) and perceived ease of use (PEOU) are important mediating factors in transferring the four SAED-Tech dimensions into organizational benefits (OB). The positive and statistically significant relationship of all the indirect paths suggests that strategic alignment (SA), artificial intelligence (AI), enterprise digitization (ED), and data-driven optimization (DO) have the effect on performance outcomes mainly due to their role in influencing the user experience.

One of the user satisfaction-based mediations, the data-driven optimization (DO → US → OB), had the most significant effect (β= 0.12), indicating that the greater the companies are in the process of optimizing and refining the digital processes, the greater the satisfaction produced, and the higher the performance is enhanced. Similarly, both strategic alignment and AI indicated significant, but slightly smaller indirect effects via US. The PEOU-mediations also showed significant effects in Table 6, where DO -P EOU -OB was the most powerful axis ((β=0.11). This means that in cases where digital systems are created to be user friendly and easy to operate the optimization processes are more effectively converted into a quantifiable organizational value. Ed and AI came right behind, which proves that ease of implementation is significant as much as technological capability itself.

All in all, the homogenous nature of partial mediation in each and every path proves that both user satisfaction and ease of use are necessary mechanisms, not byproducts, unlocking the strategic value of digital transformation initiatives. MICOM procedure also established configure, compositional and scalar invariance. The multi-group analysis findings are summarized in Table 6, highlighting differences across firm size and geographic context. The non-significant p -values (all 0.05) from permutation tests (5,000 runs) support the group equivalence. MGA found large differences by the firm size and location: digitization was more effective in SMEs ((β= 0.39) than in large companies ((β= 0.25) and in GCC organizations ((β= 0.31) than in Jordanian corporate entities ((β= 0.19).

Table 6. Multi-group analysis results

Path	SMEs (β)	Large Firms (β)	Jordan (β)	GCC (β)
ED → PEOU	0.39***	0.25*	0.28*	0.33**
AI → US	0.22**	0.25**	0.19*	0.31**

(*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$)

The endogeneity problem was also not detected through the R. Gaussian copula procedures that were conducted to perform robustness diagnostics. The full collinearity VIF measure did not exceed 3.3 which also did not show any common, method bias. They also used FIMIX-PLS (2-5 segment solutions), which did not indicate constant unobserved heterogeneity; AIC3 and BIC supported the single segment solution.

Besides the SEM results, optimization feedback loops were studied by means of the simulations with MATLAB and Python. The dynamic effects of optimization maturity are visualized in Figure 3, demonstrating nonlinear growth in organizational benefits. Findings indicated nonlinear increments: 5% change in the degree of maturity of optimization matched to 8% change in projected organizational benefits, a 10 per cent change projected a 15 per cent change over time and a 20% projected a nearly 30 per cent change over time. The possible implications of such findings are the compounding and dynamic aspect of the optimization part of the US military SAED-Tech.

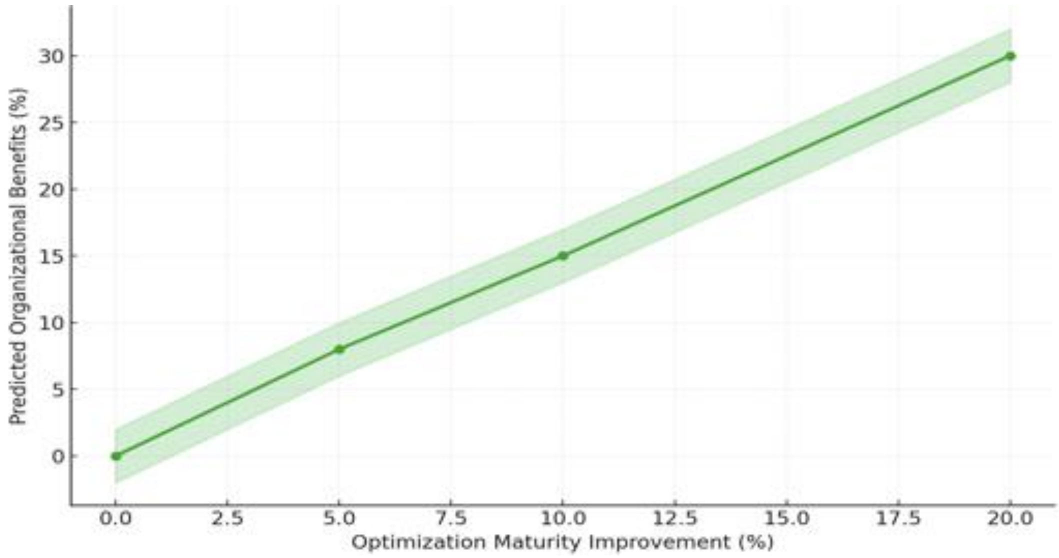

Figure 3. Simulation of optimization impact on benefits

4. Discussion

4.1. Overview of main findings

This study carefully assessed and confirmed the SAED-Tech model according to which, the four enabling factors, namely, the strategic alignment, artificial intelligence, enterprise digitization, and data-driven optimization, get mixed with the mediating role of variables that relate to user-experience. Demystified on the basis of Partial Least Squares Structural Equation Modeling (PLS-SEM), the results indicated the mechanism by which these facilitating technologies would have a substantial impact on user satisfaction and presumed ease of use, both potent antecedents of organizational gains. The model explained 64% variance of satisfaction, 59% of variance of ease of use and 72% of variance of benefits and demonstrated significant magnitude of explanatory power [43].

Besides the cross-sectional results, the simulation experiments provided more reasons to consider the dynamic and progressive nature of the resulting gains with the help of optimization interventions. Incremental gains in the optimization model were disproportionately large: a supposedly small +5% optimization would result in an expected +8% increase in benefits, a +10% increase would result in an expected +15 increases and actually +30 increases in benefits. All things considered, these outcomes hint at the existence of the SAED-Tech model specifically defining the short-term perceptual processes related to technological adoption and the long-term performance trajectories of digitization [44].

4.2. Theoretical contributions extending the technology acceptance model (TAM)

TAM identifies perceived usefulness and ease of use as adoption determinants [16], [45]. SAED-Tech builds on this by stipulating that user satisfaction is not an end-point but a mediated motivator of sustained advantage. This reframing is consistent with recent exhortations to treat satisfaction as an important linkage to value realization [46].

Integrating the resource-based view (RBV)

The RBV posits information technology assets can produce competitive advantage where they are distinct, scarce, valuable, and non-substitutable [8]. However, little information is provided by it on the mechanisms by which digital assets are literally converted to performance. SAED-Tech balances the scale by introducing user satisfaction and usability as conversion mechanisms by which aligned, digitized, and optimized assets produce tangible results [47].

Refining the IS success model

Classically, the IS Success Model considers user satisfaction to be an end measure of success [30]. SAED-Tech also does the same but places satisfaction on the causal mediator side to determine whether investments on AI, digitization, and optimization produce value generation [23].

Complementing task-technology fit (TTF)

TTF is about technology-task match [15]. While valuable, it does not take neither strategic alignment nor learning loops of optimization into consideration. SAED-Tech has them both and shows that the change is more about adaptation and constant tuning beyond fitting [48]. Through integration of these views, SAED-Tech gives an inclusive framework that connects micro-level acceptance theory to macro-level performance perspectives on organizations and provides theoretical originality [27].

4.3. Comparing PLS-SEM and simulation findings

What is unique about this study is the triangulating PLS-SEM with simulation. PLS model statistically confirmed the hypothesized relationships through statistical validation and validated significant mediated paths and substantial prediction power (PLSpredict outclassing LM on all indicators) [27].

Simulation provided a dynamic complement by showing how cumulative benefits build up over time. While PLS produces linear estimates of instantaneous relationships, the simulation provided nonlinear growth, especially within the improvements due to optimization [44]. Instead of contradiction, this difference is an indication of methodological complementarity: PLS checks instantaneous mechanisms, and simulation identifies growth over time. Having this double perspective reinforces belief within the results and highlights the explanatory depth of the model.

4.4. Practical implications

For managers, the results highlight digitization and optimization as high-leverage levers. Small incremental improvements in optimization maturity produce compounding returns in the long run [22]**.** Similarly, digitization has high leverage over usability, particularly among SMEs [12], and therefore intuitive digital platforms can stimulate organizational performance. The MGA estimates indicate that the impact of AI on satisfaction is more pronounced in the GCC nations compared to Jordan due to variations within infrastructure and level of regulatory maturity [3]. SAED-Tech can be used by policy-makers to create personalized digital policies where AI uptake improves efficiency and confidence. Digitization affected perceived ease of use more considerably in SMEs, thereby also supporting its adoption catalyst function. SMEs will therefore want to invest more in user-friendly digital tools [49]. Large companies would likely already be using digitization and will want to direct attention to the optimization feedback loops to obtain more value from currently existing infrastructures [9].

4.5. Boundary conditions and contextual nuances

The findings also showed group-level resilience where MICOM validated invariability. Subgroup analysis also showed that digitization was more important to SMEs and AI more to the GCC region. Such variations imply that the findings of SAED-Tech are generalizable but contextually sensitive [28]. Simulation also highlighted further that the aggregation of benefits is nonlinear, meaning organizations with more digital maturity can realize faster performance benefits [47], whereas those further down the line can do so more slowly. This is where temporal and contextual dynamics play a more critical role within digital strategy.

4.6. Importance of the model

The current study applies the blending of the simulation and the PLS-SEM approaches to achieve dual validation for SAED-Tech. The simulation method reveals time-dependent amplification, whereas the PLS method reveals the presence of strong mediated pathways. This is in contrast with other models like TAM, RBV, IS Success, and TTF, which explain an integrative and dynamic model whereby this integrative and dynamic model does not only explain the determinants of user adoption, but also the dynamics by which this integration and adaptation leads to the build-up of sustainable organizational value [46], [28]. Therefore, SAED-Tech is not just a theoretical framework and research agenda, but a made-to-order practical toolkit, which can be of invaluable use to scholars, managers, and policy analysts of emerging as well as established economies.

5. Conclusion and recommendations

The SAED-Tech model was defined and proven by a research focusing on the combination of Strategic Alignment, Artificial Intelligence, Enterprise Digitization, and Data-Driven Optimization to embrace the digital transformation that leads to organizational value. Under the effects of PLS-SEM, the model demonstrated a strong explanation ability in which User Satisfaction and Perceived Ease of Use proved to be the best mediators. Step-wise optimization maturity also demonstrated by supplemental simulation that cumulative progress in optimization can be attained to enable sustainable long-term improvement in performance. These outcomes, both individually and in combination, render SAED-Tech a comprehensive framework that includes short-term perceptual drivers and dynamic organizational outcomes and is based on the previous theories such as TAM and RBV and IS Success and TTF.

To make the practice, the results suggest that managers should consider the process of optimization as a continuous feedback loop and not a single investment since even maturity gains that are incremental result in exponential returns. The user-friendly digitization should become the priority of SMEs to guarantee adoption and satisfaction increase, and optimization should become the priority of larger companies to receive the most out of the already established infrastructures. The policymakers should localize their digital transformation policies: new markets should invest into basic digitization and digital literacy, and more advanced economies should use the adoption and optimization of AI to generate competitiveness. Trust and expedited adoption can also be achieved through sandboxing and open frameworks.

In the case of research, the SAED-Tech model opens up a number of prospects. The longitudinal design could be used in further research to capture the simulation-exposed compounding effects, apply the model to test whether the simulations can be generalized to other industries among others such as healthcare or schooling, or to use cybersecurity readiness as a moderator. Nonlinear dynamics also may be directly included in the capture, by incorporating advanced analysis methods, such as machine learning with SEM.

All in all, SAED-Tech is both theoretically and managerially innovative. It bridges the user acceptance gap on the micro-level and the outcome measure gap on the macro-level to give an end-to-end roadmap to managers, policymakers and academics. Integrating both the rigor of PLS-SEM and active simulation, the model does not only show how adoption takes place, but also how it leads to long-term performance improvements and, therefore, is the ultimate resource to help digital transformation in numerous environments. This paper shows a very crucial connection between micro-level user perceptions and macro-level organizational performance, providing a detailed account of the digital value creation.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

Funding information

The authors extend their appreciation to the Deanship of Research and Graduate Studies at King Khalid University for funding this work through a large-group Research Project under grant number (RGP.2/372/47).

Author contribution

The contribution to the paper is as follows: Saed Adnan Mustafa, Tahreer M. Abu Hmeidan: study conception and design; Tahreer M. Abu Hmeidan, Majd Alhawamdeh, Reda Abdelfattah Mohammad: data collection; Saed Adnan Mustafa, Majd Alhawamdeh, Reda Abdelfattah Mohammad, Alanoud M. Mbaidin, Farah Shraideh: analysis and interpretation of results; Saed Adnan Mustafa, Alanoud M. Mbaidin, Farah Shraideh: draft preparation. All authors approved the final version of the manuscript.

Ethical approval statement

Ethical approval is not applicable for this research.

Informed consent

Informed consent for the publication of personal data in this article was not obtained because the manuscript does not contain any identifiable images, personal details, or other distinguishing characteristics, and all information has been anonymized

References

[1] J. Holmström, “Digital transformation research: Current state and future directions,” Computers in Industry, vol. 127, Art. no. 103390, 2021. https://doi.org/10.1016/j.compind.2021.103390

[2] M. Bouwmans, X. Lub, M. Orlowski, and T.-V. Nguyen, “Developing the digital transformation skills framework: A systematic literature review approach,” PLOS ONE, vol. 19, no. 7, 2024. https://doi.org/10.1371/journal.pone.0304127

[3] N. S. Al-Kahtani et al., “Digital health transformation in Saudi Arabia: A cross-sectional analysis using the HIMSS digital health indicator,” Digital Health, vol. 8, 2022, Art. no. 20552076221117742. https://doi.org/10.1177/20552076221117742

[4] U. C. Kandasamy, “Ethical leadership in the age of AI,” arXiv preprint arXiv:2410.18095, 2024. https://doi.org/10.48550/arXiv.2410.18095

[5] J. Reis and N. Melão, “Digital transformation: A meta-review and guidelines for future research,” Heliyon, vol. 9, Art. no. e12834, 2023. https://doi.org/10.1016/j.heliyon.2023.e12834

[6] H. K. Alawamleh et al., “The e-leadership transformation in corporate environment,” Human Systems Management, vol. 44, no. 2, pp. 249–267, 2025.

[7] 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. https://doi.org/10.2307/249008

[8] J. Barney, “Firm resources and sustained competitive advantage,” Journal of Management, vol. 17, no. 1, pp. 99–120, 1991. https://doi.org/10.1177/014920639101700108

[9] S. A. Mustafa, M. Luthia, and R. J. Al Darwashi, “Fostering the metaverse to drive digital leadership, productivity, and an inclusive work environment,” in Human Capital Management and Competitive Advantage in Tourism, Hershey, PA, USA: IGI Global, 2025, pp. 309–337. https://doi.org/10.4018/979-8-3373-0071-9.ch011

[10] T. N. Hashem, M. S. Almahairah, S. El-Taher, H. Beyari, and B. S. Al-Romeedy, “Applying green digital marketing initiatives as an approach to driving sustainable consumer behavior,” in Advances in Science, Technology and Innovation, Cham, Switzerland: Springer, 2026, pp. 283–290, https://doi.org/10.1007/978-3-032-00590-8_36.

[11] J. C. Lopes et al., “Artificial intelligence adoption in SMEs: Exploring user satisfaction and ease of use,” Journal of Small Business and Enterprise Development, vol. 31, no. 5, pp. 1150–1172, 2024. https://doi.org/10.1108/JSBED-09-2023-0331

[12] H. M. A. Al Omari, M. R. A. Kadir, R. B. Sapingi, and A. H. M. A. D. Al-Dalaien, “The dynamics of CAATs adoption in Jordan: Bridging top management support with auditor innovativeness and IT competency,” WSEAS Transactions on Business and Economics, vol. 22, pp. 20–31, 2024.

[13] C. Climent, F. J. García-Peñalvo, and R. Therón, “Digital transformation and higher education: Toward a framework of institutional benefits,” Education and Information Technologies, vol. 29, no. 2, pp. 1623–1642, 2024. https://doi.org/10.1007/s10639-023-12164-3

[14] S. A. Mustafa and F. M. Shehada, “Financial fraud detection based on predictive analytics in high-frequency digital payment channels,” in Proceedings of the 3rd International Conference on Cyber Resilience (ICCR), 2025, pp. 1–7. https://doi.org/10.1109/ICCR67387.2025.11291756

[15] D. L. Goodhue and R. L. Thompson, “Task-technology fit and individual performance,” MIS Quarterly, vol. 19, no. 2, pp. 213–236, 1995. https://doi.org/10.2307/249689

[16] V. Venkatesh, “Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion,” Information Systems Research, vol. 11, no. 4, pp. 342–365, 2000. https://doi.org/10.1287/isre.11.4.342.11872

[17] W. H. DeLone and E. R. McLean, “The DeLone and McLean model of information systems success: A ten-year update,” Journal of Management Information Systems, vol. 19, no. 4, pp. 9–30, 2003. https://doi.org/10.1080/07421222.2003.11045748

[18] A. Abu-Al-Aish, “Exploring technical quality factors that enhance mobile learning applications services using data mining techniques,” International Journal of Information and Communication Technology Education, vol. 17, no. 4, pp. 1–23, 2021.

[19] D. J. Teece, “Business models and dynamic capabilities,” Long Range Planning, vol. 51, no. 1, pp. 40–49, 2018. https://doi.org/10.1016/j.lrp.2017.06.007

[20] A. Artene et al., "Unlocking business value: Integrating AI-driven decision-making in financial systems," Electronics, vol. 13, no. 15, Art. no. 3069, 2024. https://doi.org/10.3390/electronics13153069

[21] J. N. Montes and J. Elizondo-García, "Faculty acceptance of generative AI in higher education," Frontiers in Education, vol. 10, Art. no. 1427450, 2025. https://doi.org/10.3389/feduc.2025.1427450

[22] A. A. A. H. Al-Dalaien and H. Kasim, "Determinants of biometric as a service (BaaS) adoption in the telecommunication companies: The mediating effect of perceived trust," in Current and Future Trends on AI Applications, vol. 1, Cham, Switzerland: Springer Nature Switzerland, 2025, pp. 411–430.

[23] S. Petter, W. DeLone, and E. McLean, "The past, present, and future of IS success," Journal of the Association for Information Systems, vol. 21, no. 6, pp. 1253–1272, 2020. https://doi.org/10.17705/1jais.00649

[24] D. R. Cavalcanti, T. Oliveira, and F. D. O. Santini, "Drivers of digital transformation adoption: A weight and meta-analysis," Heliyon, vol. 8, no. 2, Art. no. e08911, 2022. https://doi.org/10.1016/j.heliyon.2022.e08911

[25] J. Vrana and R. Singh, "Digitization, digitalization, and digital transformation," in Handbook of Nondestructive Evaluation 4.0, Cham, Switzerland: Springer International Publishing, 2021, pp. 1–17, https://doi.org/10.1007/978-3-030-48200-8_1

[26] E. Tjondro and H. Tjaraka, "How does market-based governance influence sustainable tax behaviour? Evidence from tax haven utilisation and tax avoidance," International Journal of Sustainable Economy, vol. 16, no. 1, pp. 45–66, 2024. https://doi.org/10.1504/IJSE.2024.136316

[27] P. C. Verhoef et al., "Digital transformation: A multidisciplinary reflection and research agenda," Journal of Business Research, vol. 122, pp. 889–901, 2021. https://doi.org/10.1016/j.jbusres.2020.09.062

[28] Y. K. Dwivedi et al., "Metaverse beyond the hype: Multidisciplinary perspectives," Technological Forecasting and Social Change, vol. 186, Art. no. 122146, 2023. https://doi.org/10.1016/j.techfore.2022.122146

[29] H. Schwaeke et al., "AI adoption in SMEs," Journal of Small Business Management, vol. 63, no. 3, pp. xx–xx, 2025.

[30] H. Alhanatleh, A. Khaddam, F. Abudabaseh, M. Alghizzawi, and A. Alzghoul, "Enhancing the public value of mobile fintech services through cybersecurity awareness antecedents," Investment Management and Financial Innovations, vol. 21, no. 1, pp. 417–429, 2024. https://doi.org/10.21511/imfi.21(1).2024.33

[31] S. A. Mustafa and F. M. F. Shehada, "Harnessing AI tools: The transformation of digital marketing techniques through deep learning and machine learning," in Studies in Big Data, vol. 178, Cham, Switzerland: Springer, 2026, pp. 121–131. https://doi.org/10.1007/978-3-031-97613-1_11

[32] M. Yi and H. Choi, "What drives the acceptance of AI technology? The roles of expectations and experiences," arXiv preprint arXiv:2306.01234, 2023. [Online]. Available: https://arxiv.org/abs/2306.01234

[33] T. Ochuba, S. Nwachukwu, and A. Adebayo, "Digital transformation and regulation: The role of compliance in user trust," Technology in Society, vol. 76, Art. no. 102398, 2024. https://doi.org/10.1016/j.techsoc.2023.102398

[34] V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," Decision Sciences, vol. 39, no. 2, pp. 273–315, 2008, https://doi.org/10.1111/j.1540-5915.2008.00192.x.

[35] M. A. Vasarhelyi and S. Romero, "Cloud computing, big data, and continuous auditing: Opportunities for accounting and assurance," Accounting Horizons, vol. 28, no. 2, pp. 409–422, 2014. https://doi.org/10.2308/acch-50679

[36] D. J. Teece, Dynamic Capabilities and Strategic Management: Organizing for Innovation and Growth, 2nd ed. Oxford, U.K.: Oxford University Press, 2021.

[37] J. N. N. Ugoani, “Digital transformation and organizational performance: The mediating role of customer satisfaction,” International Journal of Economics and Business Research, vol. 26, no. 3, pp. 289–306, 2023. https://doi.org/10.1504/IJEBR.2023.128734

[38] A. B. Doumi, F. E. Abualadas, M. M. A. Shquier, M. Asassfeh, B. M. Elzaghmouri, and K. M. Alhawity, “New extracted features to recognize faces affected by occlusions and common variations,” Journal of Advanced Research in Applied Sciences and Engineering Technology, vol. 34, pp. 211–239, 2024.

[39] T. N. Hashem, S. S. Badrakhan, E. A. Shaban, Y. Öcel, A. Albattat, A. Kumar, and J. A. Al-Gasawneh, “How can playable ads support digital advertising: Content, frequency, and engagement,” in Advances in Science, Technology and Innovation, Cham, Switzerland: Springer, 2026, pp. 291–298. https://doi.org/10.1007/978-3-032-00590-8_37

[40] J. F. Hair Jr., G. T. M. Hult, C. M. Ringle, and M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 3rd ed. Thousand Oaks, CA, USA: Sage Publications, 2021.

[41] J. F. Hair Jr., M. Sarstedt, C. M. Ringle, and S. P. Gudergan, Advanced Issues in Partial Least Squares Structural Equation Modeling, 2nd ed. Thousand Oaks, CA, USA: Sage Publications, 2022.

[42] M. Alghizzawi, I. Ezmigna, K. Jado, K. Alzeaideen, and M. Kanan, “Theoretical perspective of artificial intelligence in digital marketing for business organizations,” in Business Analytical Capabilities and Artificial Intelligence-Enabled Analytics, vol. 1, Cham, Switzerland: Springer Nature, 2024, pp. 167–177. https://doi.org/10.1007/978-3-031-52273-4_12

[43] I. Ezmigna, M. Alghizzawi, M. Habes, and S. A. Salloum, “Application of data mining and AI for supply chain inventory forecasting,” in Generative AI in Creative Industries, Cham, Switzerland: Springer Nature, 2025, pp. 285–297. https://doi.org/10.1007/978-3-031-61573-3_18

[44] T. N. Hashem, “From insight to advantage: Harnessing the potential of marketing intelligence systems in tourism,” in Marketing and Big Data Analytics in Tourism and Events, Cham, Switzerland: Springer, 2024, pp. 1–20. https://doi.org/10.1007/978-3-031-47541-2_1

[45] V. Venkatesh, “Adoption and use of AI tools: A research agenda grounded in UTAUT,” Annals of Operations Research, vol. 308, no. 1, pp. 641–652, 2022. https://doi.org/10.1007/s10479-020-03918-9

[46] S. Mustafa, I. Abu-AlSondos, A. Salameh, W. Khabashna, A. Al-Junaidi, and A. Alkhwaldi, “The role of business intelligence in enhancing e-commerce development: The mediating effect of digital transformation,” Heritage and Sustainable Development, vol. 8, no. 1, pp. 399–414, 2026. https://doi.org/10.37868/hsd.v8i1.1403

[47] A. Rzepka, K. Kmiotek, and T. N. Hashem, “Examining marketing cyber-security in the digital age,” International Journal of Data and Network Science, vol. 8, no. 4, pp. xx–xx, 2024.

[48] X. Zhang, M. Li, and Y. Sun, “Task-technology fit and digital transformation: An empirical study of Chinese enterprises,” Technological Forecasting and Social Change, vol. 180, Art. no. 121700, 2022. https://doi.org/10.1016/j.techfore.2022.121700

[49] S. Mittal, M. A. Khan, D. Romero, and T. Wuest, “A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs),” Journal of Manufacturing Systems, vol. 49, pp. 194–214, 2018. https://doi.org/10.1016/j.jmsy.2018.10.005

Appendix
Measurement Items for SAED-Tech Constructs

Construct	Measurement Items (Likert scale: 1 = strongly disagree, 5/7 = strongly agree)	Source(s)
Strategic Alignment (SA)	SA1: Our IT and digital strategies are aligned with business objectives. SA2: Digital initiatives support the organization's long-term vision. SA3: Top management integrates digital priorities into strategic planning.	Reis & Melão (2023); Trenerry et al. (2021)
Artificial Intelligence (AI)	AI1: AI tools improve the quality of decision-making in our organization. AI2: AI systems complement human expertise rather than replace it. AI3: AI enhances organizational agility and responsiveness.	Artene et al. (2024); Montes & Elizondo-García (2025)
Enterprise Digitization (ED)	ED1: Our organization has digitized most of its core processes. ED2: Digital platforms facilitate collaboration across departments. ED3: Cloud and mobile-first strategies enhance our efficiency.	Vrana & Singh (2021); Bouwmans et al. (2024)
Data-Driven Optimization (DO)	DO1: We use data analytics to continuously improve business processes. DO2: Performance monitoring is based on real-time data. DO3: Data insights are integrated into strategic decision-making.	Best (2018); Abu-AlSondos et al. (2024)
User Satisfaction (US)	US1: I am satisfied with the digital systems used in my work. US2: The digital tools meet my expectations. US3: Overall, I am pleased with the outcomes of using digital technologies.	DeLone & McLean (2003); Chatterjee et al. (2021)
Perceived Ease of Use (PEOU)	PEOU1: Digital tools used in our organization are easy to learn. PEOU2: Interacting with digital systems is clear and understandable. PEOU3: It is easy for me to become skillful at using digital technologies.	Davis (1989); Venkatesh (2000)
Organizational Benefits (OB)	OB1: Digital transformation has improved operational efficiency. OB2: Our organization has become more innovative due to digital adoption. OB3: Overall performance has improved through digital transformation.	Teece (2018, 2021); Ugoani (2023)