“Strategic alignment as a mediator between digital transformation and innovation management in Saudi renewable energy companies”

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STRATEGIC ALIGNMENT AS A MEDIATOR BETWEEN DIGITAL TRANSFORMATION AND INNOVATION MANAGEMENT IN SAUDI RENEWABLE ENERGY COMPANIES

Abstract

This paper examines the impact of digital transformation on innovation management and strategic alignment as a mediator within Saudi Arabian renewable energy companies. A quantitative cross-sectional research design was employed with a convenience sample of 371 lower-, middle-, and senior-level managers. These respondents were involved in the implementation of digital transformation, innovation management processes, and organizational strategic planning within 45 officially licensed renewable energy companies. SmartPLS 4 (PLS-SEM) was chosen to assess the measurement and structural model. Findings demonstrate that digital transformation has a significant positive impact on innovation management ($\beta = 0.348$, $p < 0.001$), with varying effects across subdimensions of technological innovation ($\beta = 0.165$, $p < 0.001$), innovative organizational structure ($\beta = 0.160$, $p < 0.001$), and innovation strategy ($\beta = 0.139$, $p < 0.001$). Strategic alignment is significantly influenced by digital transformation ($\beta = 0.300$, $p < 0.001$), subsequently contributing to innovation management ($\beta = 0.290$, $p < 0.001$). Notably, strategic alignment partially mediates the digital transformation–innovation relationship (indirect effect: $\beta = 0.087$, $p < 0.001$), with indirect effect accounting for approximately 25%. These results suggest that digital transformation has a direct positive effect on the management of innovation by increasing technological capabilities, and strategic alignment can significantly increase the benefits of digital transformation. Overall, integration and strategic alignment between resources and capabilities enable companies to better utilize digital opportunities, tone business focus and workforce priorities, and support the role of the industry in achieving the overall objectives of Saudi Vision 2030.

Keywords digital transformation, innovation management, strategic alignment, renewable energy, Saudi Arabia, mediation analysis

JEL Classification M10, O30, Q42

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INTRODUCTION

The Saudi Arabian renewable energy industry is experiencing a revolutionary stage that is driven by the country's devotion toward clean energy production in accordance with Vision 2030. This strategic plan requires that renewable energy companies integrate digital technologies into their operations and management systems to become more efficient, competitive, and innovative. Digital transformation, which is a set of widespread implementations of digital technologies in all organizational practices, has become a priority strategic need instead of a technological upgrade. Nonetheless, the relationship between digital transformation and innovation outcomes in renewable energy remains under-researched, particularly the mechanisms by which digital efforts can be translated into tangible innovation outcomes.

The environment in which renewable energy companies operate is marked by advanced technology, increased regulatory requirements, and competition. These pressures demand that organizations be creative at all times in how they design their systems, operations, and optimization. This leads to greater use of the new digital technologies in performance enhancement and innovation assistance in most companies, such as automation technologies, predictive analytics, and real-time monitoring systems. Despite such involvement in digital tools, including automation systems, advanced analytics, and digital monitoring channels, some organizations still cannot assess the efficiency of their innovation activities (Usai et al., 2021). The presence of digital technologies does not imply that a company is sure to be more innovative. The key one is the degree of strategic clarity of such digital endeavors. Without such alignment, digital technologies may be pursued in silo and generate efficiency without delivering a sustained boost in innovation capacities.

In addition, the Saudi renewable energy managers indicated that even with massive investments in digital infrastructure, several organizations are unable to translate technological features into sustained innovation (Saudi Energy Efficiency Center, 2022). Thus, what is required is not just digitalization; the organizations must possess an integrated framework linking digital capabilities to the innovation efforts. Hence, it is not only digitalization that is desired; companies need a unified system through which digital capabilities can be integrated into their innovation activities. Nevertheless, the detailed processes by which digital transformation translates into innovation outcomes have not been well studied, especially the effectiveness of strategic alignment as a possible mediating variable in this relationship.

1. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Digital transformation is not an issue of the technology in itself; it is an entirely new approach to the structure, organization, and capabilities of the organization that would be digital-centric (Vărzaru & Bocean, 2024). Such change involves the introduction of digital technologies into organizational systems, such as cloud computing, artificial intelligence (AI), the Internet of Things (IoT), and data analytics, with the intent of creating value, enhancing efficiency, and building competitive advantage. Digital transformation in the field of renewable energy is embodied in three interconnected aspects of operation: automation of processes under the IoT and robotics in the area of routine operations; real-time monitoring of equipment through energy generation facilities with further developments of sensor networks; predictive maintenance algorithms that determine signs of equipment prior to failure; and optimization of energy distribution networks driven by data, which balances the supply and demand in real-time (Wrat et al., 2025; Iqbal et al., 2019; Uddin et al., 2024). The capabilities allow the renewable energy companies to maximize the efficiency of their operations, minimize the downtime of their equipment, and optimize the use of their assets in solar, wind, and other renewable platforms. The process automation dimension of renewable energy implies the use of automation systems for routine maintenance operations, facility surveillance, and maintenance schedules. It has also been shown that automation in the work of the energy sector saves money on its operation and, at the same time, increases productivity and accuracy in managing (Si et al., 2023). Ajiga et al. (2024) define that the automation of software in particular ways promotes efficiency in industrial operations, eliminates the involvement of humans in various areas, and minimizes the error rates in critical processes. Smart grids are another example of the transformative power of automation, enabling real-time energy balancing between production and consumption and the easy integration of renewable sources into the wider electrical system (Mahmood et al., 2024). Mitchell et al. (2022) noted that automation and artificial intelligence-based systems can significantly enhance the management of renewable energy facilities by minimizing downtime and increasing the reliability of the system. Automation is not limited to physical systems but also extends to workflow automation in administrative processes, reducing manual involvement in data processing, report generation, and activity scheduling, allowing human resources to be engaged in more strategic activities that involve judgment and creativity. Renewable energy organizations have found it specifically useful to incorporate robotic process automation to process large amounts of operational data, generate compliance reports, and handle communication with suppliers. These functions once demanded a significant amount of administrative resources (Chen et al., 2025). Boucif et al. (2025) show that AI-driven automation of renewable energy monitoring systems enhances the accuracy of detecting anomalies in the operation of the systems and, at the same time, reduces the cost of operations in terms of monitoring, which is a lifetime cycle of the system.

The second important aspect of digital transformation is process optimization, which entails continuous improvement of processes using advanced analytics and machine learning. This dimension focuses on the systematic attempts to detect the inefficiencies, remove the non-value-added processes, and improve the overall performance of the processes with the help of data-informed decisions (Onwusinkwue et al., 2024). Karad and Thakur (2021) articulated a consistent process improvement of the operations within the context of renewable energy, as the continuous and efficient improvement of the energy conversion efficiency, and the decrease in the waste within the solar and wind systems, was enabled with the help of the digital analytics capabilities. Examples of process optimization in the context of renewable energy are the optimization of the energy production capacity of a system based on historical weather data and real-time measurements, the algorithmic optimization of turbine blades and the sun's position to gather the maximum energy, and the efficiency of a system with energy storage based on algorithms (Ukoba et al., 2024). The combination of Internet of Things (IoT) sensors and monitoring systems makes it possible to collect data granularly, which demonstrates the operation areas that become bottlenecks and the opportunities to improve performance, as well as the quick response to the emerging issues in functioning. Marangis et al. (2025) show that predictive analytics-based intelligent maintenance methods can significantly increase equipment life and reduce maintenance expenses, thereby creating competitive advantages in large renewable energy systems with installed bases. The result of ongoing refinement models, based on real data of operation and not past assumptions, is a competitive advantage based on incrementally better performance on large installations of renewable energy systems. Naeem et al. (2024) record that the optimization of processes in the renewable energy sector, supported by the digital transformation technologies, will raise the productivity of the assets by 20–50% in comparison with the organizations that will follow conventional operational practices, with the enhancement focused on the optimization of the energy yields and predictive maintenance.

The third critical aspect of digital transformation is data-driven decision-making, a radical shift from intuition- or experience-based decision-making to an evidence-based approach grounded in systematic analysis of available data (AL-Khatib, 2024). This change needs the creation of organizational data collection capabilities across various sources, integration between distinct systems, complex analysis based on statistical and machine learning methods, and interpretation of the results of the analytical process to make strategic decisions (Sarioguz & Miser, 2024). Korherr et al. (2022) determine that those organizations that practice data-driven decision-making have much better forecast accuracy and risk management in comparison to other organizations that base their practices on managerial experience and intuition. In the case of renewable energy, data-driven strategies allow predicting energy demand trends at various time scales, determining the most promising locations for new plants based on past resource and infrastructure accessibility, and quantifying operational risks using predictive analytics (Bello et al., 2024). Singh et al. (2024) observed that predictive analytics features can be used to increase the reliability of renewable energy systems by means of proper weather forecasting and demand prediction to facilitate better energy storage management and grid integration planning. This shift to data centricity requires the development of organizational capabilities that extend far beyond business intelligence and a dashboard report to include advanced analytics, statistical proficiency, and data science competency that can assist in identifying actionable insights to complex operational and market information. Udo et al. (2024)

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demonstrate that those organizations that implement large data-based decision models within the framework of renewable energy are more efficient in their operations, have more effective strategic planning, and identify risks as compared to organizations with low data analytics.

However, the concept of innovation management is crucial in driving digital transformation. Innovation management can be defined as the organized endeavors by which companies create, review, and execute new concepts, technologies, and practices that improve value generation and competitiveness (López & Oliver, 2023). Organizations with properly established innovation management systems, including transparent R&D cycles, aligned project portfolios, and formalized evaluations, are more likely to record greater application of the technology and more coherent improvements in performance (Campos-Guzman et al., 2019; Vanegas-Cantarero et al., 2022; Goli, 2024). These results indicate that the success or failure of innovation in renewable energy settings is not only determined by the technologies, but also the managerial systems that facilitate their emergence and implementation. Therefore, the strategy of innovation gives the general focus that determines resource mobilization and organizational decisions regarding the nature of the innovation opportunities to be undertaken. Studies indicate that well-defined innovation strategies can enable organizations to react better to market changes, enhance internal responsiveness, and invest in the most significant initiatives (Veselica Celić, 2025). A focused strategy, be it toward the further development of storage technologies, the enhancement of photovoltaic efficiency, or the further development of new financing models, has been associated with superior commercialization performance and the increased compatibility with policy and investment conditions in renewable energy companies (Wen et al., 2022; Hasan et al., 2023). In the absence of such strategic clarification, innovation activities are likely to be disjointed and ineffective.

Technological innovation further focuses on internal development, but it is more open innovation ecosystems, in which renewable energy companies jointly develop solutions with various stakeholders, such as suppliers, customers, and technology vendors (Greco et al., 2017). Digital twin technologies are further revolutionary, as they enable organizations to develop virtual representations of real assets that can be optimized indefinitely, the actions of which can be tested in different scenarios as well as maintained in advance without interfering with the real processes (Bassey et al., 2024). Renewable energy technological innovation is characterized by more modular design strategies that permit standardizing core elements and tailoring them to the needs of deployment situations (Mignacca et al., 2020). This modularity simplifies the processes and allows economies of scale as well as reconfigurations of the system quickly as technology advances or the environment around the site changes. But the principles of human-centered design are becoming increasingly important, and the understanding that the acceptance of technologies is not only a matter of technical performance but also is subject to human factors, the ease of installation, and access to maintenance (Abou-Moghli, 2025a). Here comes the importance of the innovative organizational structure, which means the way the organization has been governed, the way it has been reported to, where the decision-making power is shared, and where teams are formed, which, in combination, allow innovation to occur throughout the organization. Studies show that reduced hierarchies, cross-functional groups of experts representing different disciplinary perspectives, and fewer bureaucratic limitations on decision-making enable faster decision-making and more effective implementation of innovations (Attah et al., 2024; Firk et al., 2022; Franco & Landini, 2022). Good structure in renewable energy organizations is one that removes silos between the engineering departments that are concerned with technical development, operations groups that are dealing with the deployed systems, and business development that is identifying the opportunities in the market. The organizational structures that enable innovation generally decrease the number of managements that must approve innovation projects, provide the ability to employees and teams at the frontline to spot opportunities of improvement and implement them, and develop spaces, both physical and virtual, in which workers in diverse functions can convene to tackle complex issues (Rafiq et al., 2021; Hussain et al., 2022). Renewable energy development is project-intensive, and structural decisions are especially relevant since project teams should incorporate numerous specialized functions during sustained development and implementation periods.

Strategic alignment plays a significant role in coordinating and combining organizational strategies, structures, systems, and capabilities (Henderson & Venkatraman, 1993). The basic strategic alignment model provides key dimensions of alignment, such as business strategy, defining competitive positioning and market focus, information technology strategy, defining technology investments and applications, organizational infrastructure, comprising structures and processes that support strategy implementation, and IT infrastructure, comprising systems and platforms that provide digital capabilities. Modern understandings of alignment are further beyond IT-business relationships and include integration of all organizational functions given that a lack of alignment in any of the key strategy–structure–system dimensions will cause organizational resistance and decrease effectiveness (Chau et al., 2020; Heracleous & Werres, 2016; Peng et al., 2021). The strategic alignment in the context of renewable energy is particularly concerned with the consistency between digital initiatives and innovation goals, where technological investments are aligned with the innovation objectives, and not implemented as stand-alone implementations that have no connection to strategic intent.

Strategic alignment has to be established and maintained by a number of organizational mechanisms and processes that are in constant action to detect and eliminate misalignment (Abou-Moghli, 2025b). Studies confirm that information technology–business alignment improves organizational performance by enhancing communication between leaders and technology, unifying objective setting, fostering a shared understanding of strategic priorities, and coordinating resource allocation, ensuring that investment is directed toward agreed-upon objectives (Slim et al., 2021). The alignment process includes governance structures, in which both the business and technology leaders concur on strategic decisions, synchronized planning processes that create both digital and business strategies, and feedback mechanisms that track the quality of alignment and detect drift among strategies before operational issues are caused when the strategies are misaligned (Adama et al., 2024; Pérez et al., 2021; Shatem & Abou-Moghli, 2024). Adama et al. (2024) noted that companies that exhibit effective strategic alignment are better placed in terms of their capacity to convert technological investments into actual business value, in terms of tangible results of innovations and market competitiveness.

In general, digital transformation establishes the background organizational capabilities that facilitate innovation through analysis and prototyping infrastructure that increases the range of innovations that can be achieved by organizations. Nevertheless, technological capabilities do not necessarily create innovative activities; organizations need to focus these capabilities on innovation priorities that are of strategic importance to the company and establish organizational conditions favorable to the creation and adoption of innovation. Hence, strategic alignment is an important factor that connects digital capabilities and drives innovation outcomes by ensuring that technological potential is translated into meaningful innovation activity. Based on prior research and theoretical underpinnings, the paper examines the impact of digital transformation on innovation management and strategic alignment as a mediator within Saudi Arabian renewable energy companies (Figure 1).

Accordingly, the following hypotheses arise:

H1: *Digital transformation has a positive and significant effect on innovation management in Saudi renewable energy companies.*

H1a: *Digital transformation has a positive and significant effect on innovation strategy.*

H1b: *Digital transformation has a positive and significant effect on technological innovation.*

H1c: *Digital transformation has a positive and significant effect on innovative organizational structure.*

H2: *Digital transformation has a positive and significant effect on strategic alignment.*

H3: *Strategic alignment has a positive and significant effect on innovation management.*

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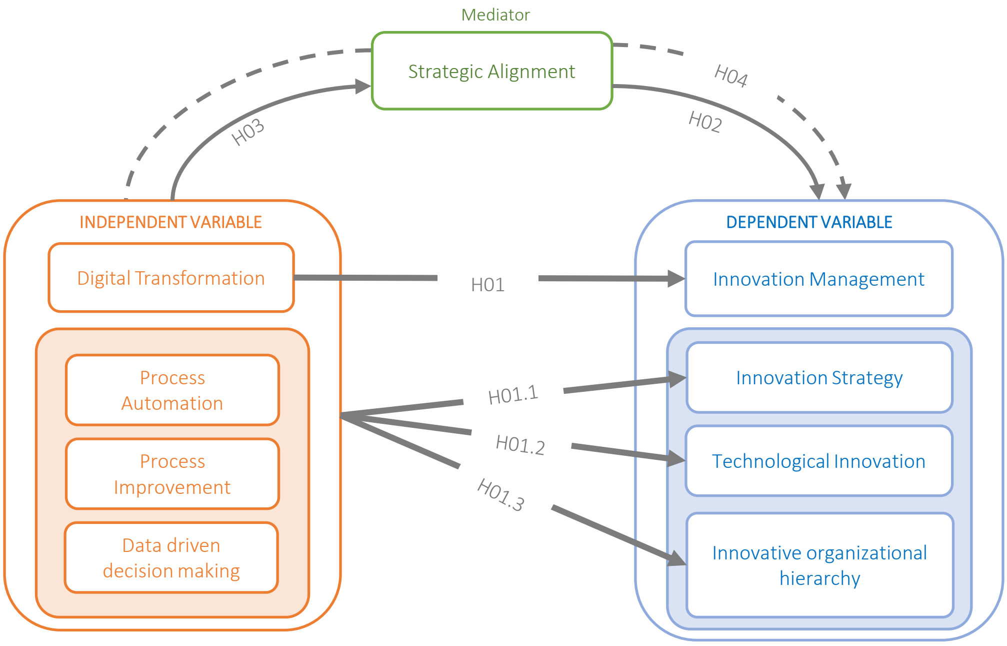

Figure 1. Conceptual model

H4: Strategic alignment partially mediates the relationship between digital transformation and innovation management.

2. METHODS

The causal descriptive approach is suitable when evaluating factors that have a causal and complex correlation with the phenomenon at hand. A cross-sectional structured questionnaire was administered to test the relationships between digital transformation, strategic alignment, and innovation management. The study was conducted among Saudi Arabian renewable energy companies (wind power and solar power generation) licensed by the Saudi Electricity Regulatory Authority (Table A1, Appendix A), which consists of about 45 organizations employing about 139,000 employees. The sampling method used a convenience sampling approach, resulting in 371 respondents. This sample was chosen because of its direct involvement in the digital transformation initiatives, innovation management, and strategic decision-making. The paper employed the sample size table constructed by Krejcie and Morgan (1970) and the formula of Cochran (1977); thus, a population of 383 is deemed applicable. This is a variance of less than 4% of the recommended threshold, which is a small variation in the target sample size that is tolerated in survey research, as long as statistical power is sufficient and the sample size is within the recommended range (Bartlett et al., 2001).

A structured questionnaire was used to measure the dimensions of digital transformation (independent variable), strategic alignment (mediating variable), and innovation management (dependent variable). Digital transformation was measured using 15 items, broken down into three dimensions: process automation (5 items), process improvement (5 items), and data-driven decision-making (5 items). The measure of strategic alignment consisted of 9 items. Innovation management was measured using 15 items across innovation strategy (5 items), technological innovation (5 items), and innovative organizational structure (5 items). All were measured using five-point Likert scales (1 = strongly disagree; 5 = strongly agree). Both the measurement model and the structural model were tested in SmartPLS 4 (PLS-SEM).

Table 1 illustrates that the sample comprised 371 respondents. Regarding gender, the majority were men (64.2 %, n = 238), and 35.8% (n = 133) were female. In terms of work experience, 21.0% (n = 78) had a work experience of less than five years, 38.3% (n = 142) had between 5–10 years, 26.4% (n = 98) had between 10–15 years, and 14.3% (n =

Table 1. Respondent's profile

Variable	Categories	Frequencies	Percentages
Gender	Female	133	35.8%
	Male	238	64.2%
Experience	Less than 5 years	78	21.0%
	From 5 to less than 10 years	142	38.3%
	From 10 to less than 15 years	98	26.4%
	15 years and over	53	14.3%
Qualifications	Diploma	10	2.7%
	Bachelor's degree	255	68.7%
	Postgraduate	106	28.6%
Managerial Level	Lower management	210	56.6%
	Middle management	131	35.3%
	Senior management	30	8.1%

53) had 15 years and above. As for education level, most had a bachelor's degree (68.7%, n = 255), followed by a postgraduate degree (28.6%, n = 106), and a small percentage had a diploma (2.7%, n = 10). Regarding the managerial level, more than half of the respondents were in lower managerial positions (56.6%, n = 210), 35.3% (n = 131) were in middle positions, and 8.1% (n = 30) were in senior positions.

3. RESULTS

In order to test the measurement model, the constructs were divided into various dimensions that were operationalized, and each dimension had several measured items. The necessary indicators, such as factor loadings, mean (M) scores, standard deviations (SD), Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE), were obtained to ensure that the measurement model is adequate.

The digital transformation construct is operationalized with three dimensions, which include process automation, process improvement, and data-driven decision making. Factor loadings are high, with all items showing a value of above 0.77, which is a good sign of convergent validity. The reliability measures are good, with Cronbach's alpha within the 0.841–0.884 range, and CR exceeds 0.9. The AVE values exceed 0.66, confirming sufficient variance explained by the latent constructs. Mean values indicate that companies embrace moderate-to-high digital practices.

The innovation management construct is operationalized in three dimensions: technological innovation, strategic innovation, and innovative organizational structure. The loading of all items is higher than 0.78, showing good measurement reliability. The loading values for all items are above 0.78, indicating good measurement reliability. Cronbach's alpha value lies between 0.857 and 0.897, and the CR value is greater than 0.9, which depicts internal consistency. AVE is greater than 0.63, confirming convergent validity. Mean scores indicate moderate involvement in strategic, technological, and organizational innovation practices.

Strategic alignment has strong factor loadings (0.737–0.810), indicating sufficient convergent validity, with Cronbach's alpha (0.915) and the CR (0.945) suggesting high internal consistency. The AVE (0.595) indicates good variance, and the mean scores (3.30–3.86) indicate a moderate-to-high level of alignment between the organizational strategy and processes. Overall, all constructs met or exceeded recommended thresholds, indicating a robust measurement model suitable for further structural analysis.

Discriminant validity was measured to make sure that each construct is empirically distinct from the other. The Fornell–Larcker criterion was used, where the square root of the average variance extracted (AVE) of each construct ought to be higher than the correlation of that construct with others (Fornell & Larcker, 1981). The values that satisfy this criterion indicate that the constructs exhibit greater variance among their own indicators than among the others. The results of this analysis are presented in Table 3, which depicts the square roots of AVE on the diagonal and inter-construct correlations off-diagonal.

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Table 2. Measurement model analysis

Construct	Dimension	Items	Loadings	M	SD	α (>0.7)	CR (>0.7)	AVE (>0.5)
Digital transformation	Process automation	PA1	0.777	3.686	0.888	0.872	0.907	0.662
		PA2	0.823	3.291	0.969			
		PA3	0.814	3.602	0.867			
		PA4	0.831	3.783	0.894			
		PA5	0.821	3.395	0.918			
	Process improvement	PI1	0.817	3.408	0.947	0.884	0.909	0.667
		PI2	0.787	3.676	0.855			
		PI3	0.814	3.133	0.956			
		PI4	0.837	3.571	0.902			
		PI5	0.829	3.878	0.858			
	Data-driven decision-making	DDM1	0.826	3.485	0.904	0.841	0.915	0.682
		DDM2	0.826	3.867	0.857			
		DDM3	0.832	3.212	0.977			
		DDM4	0.811	3.691	0.921			
		DDM5	0.835	3.954	0.792			
Innovation management	Strategic innovation	IM1	0.805	3.582	0.881	0.857	0.897	0.636
		IM2	0.781	3.406	0.933			
		IM3	0.807	3.773	0.883			
		IM4	0.797	3.472	0.927			
		IM5	0.797	3.691	0.861			
	Technological innovation	IM6	0.846	3.202	0.964	0.897	0.924	0.707
		IM7	0.828	3.505	0.938			
		IM8	0.830	3.102	0.975			
		IM9	0.859	3.574	0.913			
		IM10	0.842	3.270	0.945			
	Innovative organizational structure	IM11	0.814	3.401	0.935	0.869	0.905	0.656
		IM12	0.777	3.783	0.880			
		IM13	0.807	3.273	0.999			
		IM14	0.825	3.487	0.951			
		IM15	0.826	3.885	0.864			
Strategic alignment		SA1	0.741	3.298	0.986	0.915	0.945	0.595
		SA2	0.804	3.584	0.931			
		SA3	0.757	3.199	1.032			
		SA4	0.796	3.755	0.908			
		SA5	0.746	3.408	0.963			
		SA6	0.794	3.684	0.892			
		SA7	0.737	3.503	0.930			
		SA8	0.751	3.286	1.011			
		SA9	0.810	3.860	0.836			

Note: M = Mean; SD = Standard deviation; α = Cronbach's alpha; CR = Composite reliability; AVE = Average variance extracted.

Table 3. Discriminant validity result using the Fornell–Larcker criterion

Variable	Process Automation	Process Improvement	Data-driven decision making	Strategic Innovation	Technological Innovation	Innovative Organizational Structure	Strategic Alignment
Process Automation	0.814						
Process Improvement	0.310	0.826					
Data-driven decision-making	0.287	0.420	0.817				
Strategic Innovation	0.156	0.105	0.248	0.798			
Technological Innovation	0.199	0.223	0.264	0.374	0.810		
Innovative Organizational Structure	0.201	0.175	0.243	0.424	0.417	0.841	
Strategic Alignment	0.210	0.263	0.199	0.279	0.298	0.280	0.771

The results show high levels of discriminant validity in all constructs. In the case of digital transformation dimensions, process automation (√AVE = 0.814), process improvement (√AVE = 0.826), and data-driven decision making (√AVE = 0.817) all outperform their inter-relations, which have a range of r = 0.287 to r = 0.420. This confirms that they are related but distinct dimensions, with the strongest relationship between process improvement and data-driven decision-making (r = 0.420). Strategic innovation (√AVE = 0.798), technological innovation (√AVE = 0.810), and innovative organizational structure (√AVE = 0.841) show acceptable levels of discriminant validity. Strategic innovation and innovative organizational structure have little correlation (r = 0.424) as both are interconnected in theory, but this is still considerably lower than the diagonal levels of adequate distinction. Strategic alignment (√AVE = 0.771) has adequate discriminant validity with variation of the correlation of r = 0.199 to r = 0.298 with other constructs. In general, all the constructs meet the Fornell–Larcker criterion, and this confirms that the measurement model has been used to differentiate the conceptually different variables, which gives confidence in the further analysis of the structure.

Path analysis was used to determine the structural relationships between the constructs of the study. Standard deviations (SD), t-values, and *p*-values were computed to determine the strength and significance of the hypothesized relationships at a standard level. To investigate possible mediating relationships, direct, indirect, and total effects were also estimated. Path coefficients are deemed to be noteworthy when *t*-values are greater than 1.96 at *p* =0.05 (Hair et al., 2022). The results of these analyses are presented in Table 4.

Table 4. Structural model analysis

Relationship	β	SD	T Value	P Value
Digital Transformation → Innovation Management	0.348	0.043	8.034	0.000
Digital Transformation → Strategic Innovation	0.139	0.019	7.262	0.000
Digital Transformation → Technological Innovation	0.165	0.021	7.926	0.000
Digital Transformation → Innovative Organizational Structure	0.160	0.022	7.211	0.000
Digital Transformation → Strategic Alignment	0.300	0.045	6.723	0.000
Strategic Alignment → Innovation Management	0.290	0.047	6.105	0.000
Digital Transformation → Strategic Alignment → Innovation Management (Indirect Effect)	0.087	0.019	4.658	0.000
Digital Transformation → Innovation Management (Direct Effect)	0.261	0.046	5.659	0.000
Digital Transformation → Innovation Management (Total Effect)	0.348	0.043	8.034	0.000

Note: β = standardized path coefficient; SD = standard deviation. P < .001.

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The results of the path analysis, as illustrated in Table 4 and Figures 2 and 3, show that innovation management is influenced by digital transformation significantly and in a positive way (β = 0.348, t = 8.034, p < .001). The strategic innovation (β = 0.139, t = 7.262, p < .001), technological innovation (β = 0.165, t = 7.926, p < .001), and innovative organizational structure (β = 0.160, t = 7.211, p < .001) are also impacted by digital transformation significantly with positive effects.

Moreover, digital transformation has a significant positive influence on strategic alignment (β = 0.300, t = 6.723, p < .001) and further has a significant impact on innovation management (β = 0.290, t = 6.105, p < .001). Strategy alignment also plays an important role in the impact of digital transformation on innovation management (β = 0.087, t = 4.658, p < .001), indicating that strategic alignment has a moderating role in this process. Since the direct impact of digital transformation on innovation management is also considerable (β = 0.261, t = 5.659, p <.001), the mediation is partial, and digital transformation directly and indirectly affects innovation management through strategic alignment. All in all, the overall impact of digital transformation on innovation management (β = 0.348, t = 8.034, p < .001) is driven by both direct and mediated paths. Therefore, all proposed hypotheses were accepted and approved.

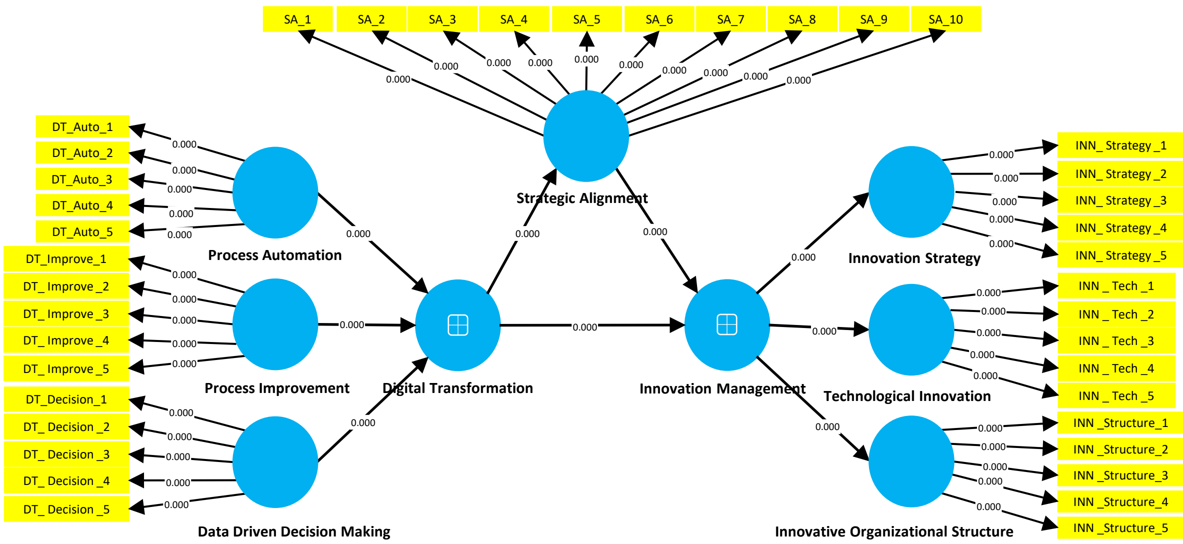

Figure 2. Structural path model for main hypotheses

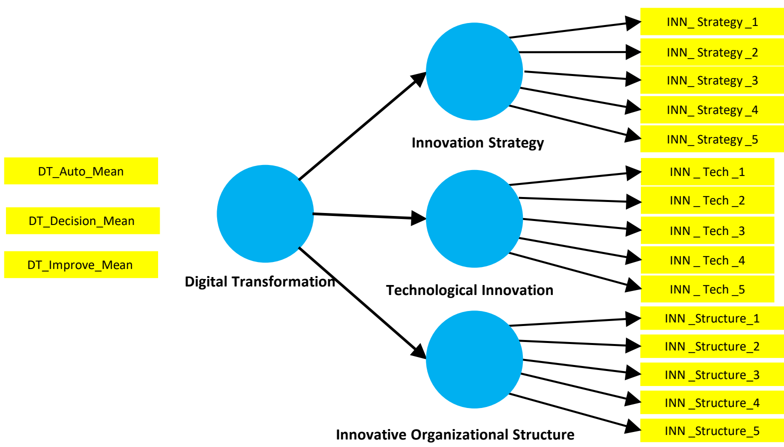

Figure 3. Structural path model for sub-hypotheses

4. DISCUSSION

The results provide empirical evidence that successful digital transformation of renewable energy organizations is a key driver of innovation management, acting both directly through digital transformation and indirectly through strategic alignment. This study shows that renewable energy organizations with a high level of integration between digital initiatives and innovation objectives achieve significantly greater innovation outcomes than those that address these priorities in isolation. Further, the study expands the digital transformation literature that focuses on technology to shed light on how strategic alignment can be instrumental in deciding whether technological investments lead to tangible benefits of innovation. It is important to note that this study identifies the mediating role of strategic alignment, which is a mechanism of how organizations make digital investments into sustainable competitive advantage in the presence of pressure on both technological and sustainability transformation in the industries.

The primary hypothesis assumes that digital transformation has a beneficial impact on innovation management ($\beta = 0.348$, $p < 0.001$). This effect is in line with the literature that reported relationships between innovation performance and the use of technology (Alkhatib et al., 2025; Vitus, 2025; Borowski, 2021; Yi et al., 2024). To drive innovation, organizations cannot rely solely on technology investments; technological capability is only a requisite condition that must be integrated with strategic direction, organizational structures, and human capabilities to deliver innovation outcomes. This finding contrasts with Li et al. (2025) and Blichfeldt and Faullant (2021), who viewed technology as a deterministic force of innovation. Instead, it is found that the effect of innovation on technology relies significantly on how organizations mobilize capabilities to achieve strategically significant aims.

The path coefficients between different dimensions of innovation management reveal that digital transformation does not play an identical role in the innovation of renewable energy companies. The greatest influence on technological innovation ($\beta = 0.165$, $p < 0.001$) is from prior research in the renewable energy industry, where companies have digital infrastructures that enable upgrades to fundamental technical processes (Bassey et al., 2024). Another body of research on photovoltaic plants, wind farms, and hybrid energy plants indicates that digitalization enhances the implementation of sensor-abundant monitoring systems, automated performance diagnostics, and AI-assisted optimization patterns (Atofarati & Enweremadu, 2025; Yalçin et al., 2023; Chiang-Guizar et al., 2025). Such capabilities not only increase the accuracy of decisions but also reduce the time in which the innovation cycle occurs, as it allows constant real-time work to be conducted. In this way, digital transformation is closely connected to technological advancement, providing a basis on which renewable energy companies develop new technologies.

Furthermore, digital transformation has a significant impact on innovative organizational structure ($\beta = 0.160$, $p < 0.001$). Energy companies integrated digital control systems, digitized workflows, and distributed asset management systems. Companies are more likely to redesign their governance processes, shift decision-making nearer to operations, and have a more modular structure. To provide an example, renewable energy operators controlling geographically scattered wind or solar resources usually incorporate remote-control centers, digital dashboards, and cross-disciplinary analytic teams, which fundamentally change the manner in which coordination and control take place (Marot et al., 2022). These changes demonstrate that structural innovation is often the by-product of digital modernization and not a planned effort by an organization.

As for the innovation strategy, the effect on it is much smaller ($\beta = 0.139$, $p < 0.001$), indicating that the strategic direction of renewable energy companies is determined by external factors that cannot be influenced by digital tools. Previous studies have indicated that regulatory incentives, grid-integration regulations, investment risk, and long-term national energy-transition goals are the predominant conditioning factors in the strategy formation in this sector (Agupugo et al., 2024; Oduro et al., 2024). Although companies use advanced digital forecasting or market-modelling models, the strategic repositioning process is usu-

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ally controlled by policy horizons, competitive auctions, and financial constraints. Thus, digital transformation seems to be facilitative in nature, but it is not the key driver of strategic innovation. This is contrary to technology-based approaches to innovation, which argue that, in the case of renewable energy, strategy is developed in response to macro-environmental forces and subsequently reinforced through digital potentials.

On the other hand, the postulated hypothesis between digital transformation and strategic alignment (β = 0.300, $p < 0.001$) shows that the application of digital technologies assists organizations in aligning resources, processes, and decision-making in a manner that aligns with strategic intent. According to Awad and Martín-Rojas (2024), digital transformation can serve as a driver of organizational learning and adaptive capacity, helping companies react more quickly to environmental shifts and market disruptions. This paper builds upon those findings by demonstrating that digital solutions (predictive analytics, real-time monitoring, and integrated information platforms) in the context of renewable energy not only make operations more efficient but also make organizations more responsive to the strategic environment. However, the effect size indicates that technology is not a driver as such, but an enabler; strategic alignment needs deliberate effort, such as aligning performance metrics, clarity of roles, and the integration of innovation objectives into strategic planning.

Furthermore, the direct relationship between strategic alignment and innovation management (β = 0.290, $p < 0.001$) confirms the fact that the closer the organizational strategy and the capabilities of organizations are aligned, the more successful the implementation of innovation initiatives becomes. It can be supported by previous studies that have demonstrated significance to the alignment as the process of converting knowledge and digital abilities into actual innovation deliverables (Sarwar et al., 2024). Along with facilitating coordination, alignment organizations should also offer a setting in which experimentation, cross-functional collaboration, and risk-taking are premeditated, rather than improvising, as this is likely to result in successful innovation. Such alignment of renewable energy companies, on the one hand, ensures that the technological upgrades, digital process improvements, and resource allocation decisions of the organization are all aligned with its long-term sustainability and competitive goals, which explains the significance of the interdependence between the strategy, structure, and the capability to innovate.

The mediation analysis indicates that strategic alignment is a significant process through which digital transformation enhances the process of innovation management in renewable energy organizations. The positive and important indirect effect ($b = 0.087$, $p < .001$) demonstrates that the effect of digital transformation is not only due to its direct technical benefits but is also reinforced when digital efforts are coordinated with the organizational focus. Given that renewable energy firms operate under a controlled, technologically varied, and geographically diffused environment, alignment ensures that digital tools are incorporated in the decision-making process, distribution of resources, and innovation agenda rather than being regarded as a distant technological enhancement. The fact that the mediation is partial, since the direct effect is significant ($b = 0.261$, $p < .001$), shows that the digital transformation does not only result in innovation by improving the direct ability but also in the systematic integration that is achieved through strategic alignment. The specified observation proves the notion that digital transformation is never technical but a strategic undertaking; the organizations that can establish alignment mechanisms (i.e., coherent planning, governance structure, and a set of shared performance metrics) are far more effective at turning digital investments into tangible results of innovation.

CONCLUSION

This study examines the impact of digital transformation on innovation management and strategic alignment as a mediator within Saudi Arabian renewable energy companies. Findings confirm that technology is not enough; companies should actively combine digitalization with innovation goals to achieve the greatest good. Digital transformation directly reinforces technological innovation, innovative organizational structure, and innovation strategy, and, at the same time, improves strategic alignment, thereby further enhancing innovation output via an indirect mechanism. In practice, renewable energy companies can focus on investing in digital capabilities and on creating governance systems that connect digital strategies to innovation priorities. The implementation of technology should not isolate organizations but rather should be accompanied by the congruent integration of strategies, structures, and systems to guarantee the realization of the sustained competitive advantage in the context of Saudi Vision 2030. Future studies can focus on the different ways in which certain digital technologies (artificial intelligence, IoT, blockchain, and digital twins) dissimilarly affect innovation outcomes, on what leadership competencies are necessary to coordinate digital-innovation integration, and on the obstacles to the alignment of digital and innovation strategies present in organizations.

AUTHOR CONTRIBUTIONS

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REFERENCES

1. Abou-Moghli, A. (2025a). How human AI skills and competitive psychological climate drive organizational innovation. *Problems and Perspectives in Management, 23*(2), 679-690. https://doi.org/10.21511/ppm.23(2).2025.49
2. Abou-Moghli, A. (2025b). The role of strategic alignment and resource availability in boosting the digital capabilities of Jordanian insurance companies. *Insurance Markets and Companies*, *16*(1), 74-89. https://doi.org/10.21511/ins.16(1).2025.07
3. Adama, H. E., Popoola, O. A., Okeke, C. D., & Akinoso, A. E. (2024). Theoretical frameworks supporting IT and business strategy alignment for sustained competitive advantage. *International Journal of Management & Entrepreneurship Research*, *6*(4), 1273-1287. https://doi.org/10.51594/ijmer.v6i4.1058
4. Agupugo, C. P., Ajayi, A. O., Nwanevu, C., & Oladipo, S. S. (2024). Policy and regulatory framework supporting renewable energy microgrids and energy storage systems. *Engineering Science & Technology Journal, 5*(8), 2589-2615. https://doi.org/10.51594/estj.v5i8.1460
5. Ajiga, D., Okeleke, P. A., Folorunsho, S. O., & Ezeigweneme, C. (2024). The role of software automation in improving industrial operations and efficiency. *International Journal of Engineering Research Updates, 7*(1), 22-35. https://doi.org/10.53430/ijeru.2024.7.1.0031
6. AL-Khatib, A. W. (2024). The determinants of export performance in the digital transformation era: Empirical evidence from manufacturing firms. *International Journal of Emerging Markets, 19*(10), 2597-2622. https://doi.org/10.1108/IJOEM-08-2022-1223

7. Alkhatib, A. W., Zaid, M., & Issa, A. (2025). Antecedents and outcomes of artificial intelligence adoption on the sustainable performance: The TOE framework perspective. *Information Discovery and Delivery*. https://doi.org/10.1108/IDD-04-2025-0076

8. Atofarati, E. O., & Enweremadu, C. C. (2025). Industry 4.0 enabled calorimetry and heat transfer for renewable energy systems. *iScience, 28*(7112994). https://doi.org/10.1016/j.isci.2025.112994

9. Attah, R. U., Garba, B. M. P., Gil-Ozoudeh, I., & Iwuanyanwu, O. (2024). Cross-functional team dynamics in technology management: A comprehensive review of efficiency and innovation enhancement. *Engineering Science & Technology Journal, 5*(12). https://doi.org/10.51594/estj.v5i12.1756

10. Awad, J. A. R., & MartínRojas, R. (2024). Digital transformation influence on organisational resilience through organisational learning and innovation. *Journal of Innovation and Entrepreneurship, 13,* 69. https://doi.org/10.1186/s13731-024-00405-4

11. Bartlett, J. E., Kotrlik, J. W., & Higgins, C. C. (2001). Organizational research: Determining appropriate sample size in survey research. *Information Technology, Learning, and Performance Journal, 19*(1), 43-50. Retrieved from https://www.opalco.com/wp-content/uploads/2014/10/Reading-Sample-Size1.pdf

12. Bassey, K. E., Opoku-Boateng, J., Antwi, B. O., & Ntiakoh, A. (2024). Economic impact of digital twins on renewable energy investments. *Engineering Science & Technology Journal, 5*(7). https://doi.org/10.51594/estj.v5i7.1318

13. Bello, S. F., Wada, I. U., Ige, O. B., Chianumba, E. C., & Adebayo, S. A. (2024). AI-driven predictive maintenance and optimization of renewable energy systems for enhanced operational efficiency and longevity. *International Journal of Science and Research Archive, 13*(1), 2823-2837. https://doi.org/10.30574/ijsra.2024.13.1.1992

14. Blichfeldt, H., & Faullant, R. (2021). Performance effects of digital technology adoption and product & service innovation: A process-industry perspective. *Technovation, 105,* Article 102275. https://doi.org/10.1016/j.technovation.2021.102275

15. Borowski, P. F. (2021). Digitization, digital twins, blockchain, and Industry 4.0 as elements of management process in enterprises in the energy sector. *Energies, 14*(7), Article 1885. https://doi.org/10.3390/en14071885

16. Boucif, O. H., Lahouaou, A. M., Boubiche, D. E., & Toral-Cruz, H. (2025). Artificial intelligence of things for solar energy monitoring and control. *Applied Sciences, 15*(11), Article 6019. https://doi.org/10.3390/app15116019

17. Campos-Guzmán, V., García-Cáscales, M. S., Espinosa, N., & Urbina, A. (2019). Life cycle analysis with multi-criteria decision making: A review of approaches for the sustainability evaluation of renewable energy technologies. *Renewable and Sustainable Energy Reviews, 104,* 343-366. https://doi.org/10.1016/j.rser.2019.01.031

18. Chau, D. C. K., Ngai, E. W. T., Gerow, J. E., & Thatcher, J. B. (2020). The effects of business–IT strategic alignment and IT governance on firm performance: A moderated polynomial regression analysis. *MIS Quarterly, 44*(4), 1679-1704. https://doi.org/10.25300/MISQ/2020/12165

19. Chen, B., Li, Z., Liu, B., Zhang, L., & Huang, X. (2025). Robust optimization for smart demand side management in microgrids using robotic process automation and grey wolf optimization. *Scientific Reports, 15,* Article 19440. https://doi.org/10.1038/s41598-025-03728-8

20. Chiang-Guizar, C. D., Hernandez-Martinez, J. I., Sevilla-Camacho, P. Y., & Solis-Cisneros, H. I. (2025). Artificial intelligence and integrated optimization in the energy sector: Advances in photovoltaic system. *Revista de Energías Renovables, 12*(55). https://doi.org/10.59730/rer.v12n55a5

21. Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons. Retrieved from https://www.scirp.org/reference/ReferencesPapers?ReferenceID=1390266

22. Firk, S., Gehrke, Y., Hanelt, A., & Wolff, M. (2022). Top management team characteristics and digital innovation: Exploring digital knowledge and TMT interfaces. *Long Range Planning, 55*(3), Article 102166. https://doi.org/10.1016/j.lrp.2021.102166

23. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

24. Franco, C., & Landini, F. (2022). Organizational drivers of innovation: The role of workforce agility. *Research Policy, 51*(2), Article 104423. https://doi.org/10.1016/j.respol.2021.104423

25. Goli, A. (2024). Optimization of renewable energy project portfolio selection using hybrid AIS-AFS algorithm in an international case study. *Scientific Reports, 14,* Article 17388. https://doi.org/10.1038/s41598-024-68449-w

26. Greco, M., Locatelli, G., & Lisi, S. (2017). Open innovation in the power & energy sector: Bringing together government policies, companies' interests, and academic essence. *Energy Policy, 104,* 316-324. https://doi.org/10.1016/j.enpol.2017.01.049

27. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2022). *Multivariate data analysis* (9th ed.). Cengage Learning.

28. Hasan, M. M., Hossain, S., Mofijur, M., Kabir, Z., Badruddin, I. A., Yunus Khan, T. M., & Jassim, E. (2023). Harnessing solar power: A review of photovoltaic innovations, solar thermal systems, and the dawn of energy storage solutions. *Energies, 16*(18), Article 6456. https://doi.org/10.3390/en16186456

29. Henderson, J. C., & Venkatraman, N. (1993). Strategic alignment: A model for organizational trans-

formation. *International Journal of Information Management, 13*(4), 233-249. Retrieved from https://dspace.mit.edu/bitstream/handle/1721.1/49184/strategicalignme90hend.pdf

30. Heracleous, L., & Werres, K. (2016). On the road to disaster: Strategic misalignments and corporate failure. *Long Range Planning, 49*(4), 491-506. https://doi.org/10.1016/j.lrp.2015.08.006

31. Hussain, S., Xuetong, W., Maqbool, R., Hussain, M., & Shahnawaz, M. (2022). The influence of government support, organizational innovativeness and community participation in renewable energy project success: A case of Pakistan. *Energy, 239*(Part C), Article 122172. https://doi.org/10.1016/j.energy.2021.122172

32. Iqbal, J., Al-Zahrani, A., Alharbi, S. A., & Hashmi, A. (2019). Robotics inspired renewable energy developments: Prospective opportunities and challenges. *IEEE Access, 7,* 174898-174923. https://doi.org/10.1109/ACCESS.2019.2957013

33. Karad, S., & Thakur, R. (2021). Efficient monitoring and control of wind energy conversion systems using Internet of Things (IoT): A comprehensive review. *Environment, Development and Sustainability, 23,* 14197-14214. https://doi.org/10.1007/s10668-021-01267-6

34. Korherr, P., Kanbach, D. K., Kraus, S., & Mikalef, P. (2022). From intuitive to data-driven decision-making in digital transformation: A framework of prevalent managerial archetypes. *Digital Business, 2*(2), Article 100045. https://doi.org/10.1016/j.digbus.2022.100045

35. Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607-610. https://doi.org/10.1177/001316447003000308

36. Li, K., Cai, Y., Pei, Y., & Yuan, C. (2025). The impact of artificial intelligence adoption on firms' innovation performance in the digital era: Based on dynamic capabilities theory. *International Theory and Practice in Humanities and Social Sciences, 2*(3), 228-237. https://doi.org/10.70693/itphss.v2i3.343

37. López, D., & Oliver, M. (2023). Integrating innovation into business strategy: perspectives from innovation managers. *Sustainability, 15*(8), Article 6503. https://doi.org/10.3390/su15086503

38. Mahmood, M., Chowdhury, P., Yeassin, R., Hasan, M., Ahmad, T., & Chowdhury, N.-U.-R. (2024). Impacts of digitalization on smart grids, renewable energy, and demand response: An updated review of current applications. *Energy Conversion and Management: X, 24,* Article 100790. https://doi.org/10.1016/j.ecmx.2024.100790

39. Marangis, D., Tziolis, G., Livera, A., Makrides, G., Kyprianou, A., & Georghiou, G. E. (2025). Intelligent maintenance approaches for improving photovoltaic system performance and reliability. *Solar RRL, 9,* Article 2500289. https://doi.org/10.1002/solr.202500289

40. Marot, A., Kelly, A., Naglic, M., Barbesant, V., Cremer, J., Stefanov, A., & Viebahn, J. (2022). Perspectives on future power system control centers for energy transition. *Journal of Modern Power Systems and Clean Energy, 10*(2), 328-344. https://doi.org/10.35833/MPCE.2021.000673

41. Mignacca, B., Locatelli, G., & Velenturf, A. (2020). Modularisation as enabler of circular economy in energy infrastructure. *Energy Policy, 139,* Article 111371. https://doi.org/10.1016/j.enpol.2020.111371

42. Mitchell, D., Blanche, J., Harper, S., Lim, T., Gupta, R., Zaki, O., Tang, W., Robu, V., Watson, S., & Flynn, D. (2022). A review: Challenges and opportunities for artificial intelligence and robotics in the offshore wind sector. *Energy and AI, 8,* Article 100146. https://doi.org/10.1016/j.egyai.2022.100146

43. Naeem, G., Asif, M., & Khalid, M. (2024). Industry 4.0 digital technologies for the advancement of renewable energy: Functions, applications, potential and challenges. *Energy Conversion and Management: X, 24,* Article 100779. https://doi.org/10.1016/j.ecmx.2024.100779

44. Oduro, P., Simpa, P., & Ekechukwu, D. E. (2024). Renewable energy expansion: Legal strategies for overcoming regulatory barriers and promoting innovation. *World Journal of Advanced Engineering Technology and Sciences, 12*(1), 168-186. https://doi.org/10.30574/wjaets.2024.12.1.0208

45. Onwusinkwue, S., Osasona, F., Ahmad, I. A. I., Anyanwu, A. C., Dawodu, S. O., Obi, O. C., & Hamdan, A. (2024). Artificial intelligence (AI) in renewable energy: A review of predictive maintenance and energy optimization. *World Journal of Advanced Research and Reviews, 21*(1), 2487-2499. https://doi.org/10.30574/wjarr.2024.21.1.0347

46. Peng, G., Chen, S., Chen, X., & Liu, C. (2021). An investigation to the Industry 4.0 readiness of manufacturing enterprises: The ongoing problems of information systems strategic misalignment. *Journal of Global Information Management (JGIM), 29*(6), 1-20. https://doi.org/10.4018/JGIM.291515

47. Pérez, M. F., Berna Martinez, J. V., & Lorenzo Fonseca, I. (2021). Strategic IT alignment projects: Towards good governance. *Computer Standards & Interfaces, 76,* Article 103514. https://doi.org/10.1016/j.csi.2021.103514

48. Rafiq, M., Naz, S., Martins, J. M., Mata, M. N., Mata, P. N., & Maqbool, S. (2021). A study on emerging management practices of renewable energy companies after the outbreak of Covid-19: Using an interpretive structural modeling (ISM) approach. *Sustainability, 13*(6), Article 3420. https://doi.org/10.3390/su13063420

49. Sarioguz, O., & Miser, E. (2024). Data-driven decision-making: Transforming management in the information age. *International Research Journal of Modernization in Engineering Technology and Science, 6*(2), 1642-1643. https://doi.org/10.56726/IRJMETS49577

50. Sarwar, Z., Gao, J., & Khan, A. (2024). Nexus of digital platforms, innovation capability, and strategic alignment to enhance innovation performance in the

Asia Pacific region: A dynamic capability perspective. *Asia Pacific Journal of Management, 41,* 867-901. https://doi.org/10.1007/s10490-023-09879-4

51. Saudi Energy Efficiency Center. (2022, November 1). *Saudi Arabia advances 10 places in the 2022 Green Future Index*. Retrieved from https://www.seec.gov.sa/en/news/saudi-arabia-advances-in-2022-global-green-index

52. Shatem, M., & Abou-Moghli, A. (2024). The moderating role of perceived environmental uncertainty in the impact of corporate governance on strategy implementation: An agency theory perspective. *Uncertain Supply Chain Management, 12*(3), 1577-1588. https://doi.org/10.5267/j.uscm.2024.3.022

53. Si, G., Xia, T., Li, Y., Wang, D., Chen, Z., Pan, E., & Xi, L. (2023). Resource allocation and maintenance scheduling for distributed multi-center renewable energy systems considering dynamic scope division. *Renewable Energy, 217,* Article 119219. https://doi.org/10.1016/j.renene.2023.119219

54. Singh, R. A., Kumar, R. S., Bajaj, M., Khadse, C.B., & Zaitsev, I. (2024). Machine learning-based energy management and power forecasting in grid-connected microgrids with multiple distributed energy sources. *Scientific Reports, 14,* Article 19207. https://doi.org/10.1038/s41598-024-70336-3

55. Slim, A., Mechman, S., Omar, S., Kadhim, K. G., Ali, B. J., Hammood, A. M., & Othman, B. (2021). The effect of information technology business alignment factors on performance of SMEs. *Management Science Letters, 11*(1), 211-220. https://doi.org/10.5267/j.msl.2020.10.019

56. Uddin, M. R., Tabassum, M., Ashfaque Hossain, M. S., Hossain, M. S., & Hasan, M. (2024). Environmental monitoring system for renewable energy installations. In *2024 IEEE 3rd International Conference on Electrical Power and Energy Systems (ICEPES)* (pp. 1-5). IEEE. https://doi.org/10.1109/ICEPES60647.2024.10653487

57. Udo, W., Toromade, A. S., & Chiekezie, N. R. (2024). Data-driven decision-making model for renewable energy. *International Journal of Management & Entrepreneurship Research, 6*(8). https://doi.org/10.51594/ijmer.v6i8.1414

58. Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T.-C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy & Environment, 35*(7), 3833-3879. https://doi.org/10.1177/0958305X241256293

59. Usai, A., Fiano, F., Messeni Petruzzelli, A., Paoloni, P., Farina Briamonte, M., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research, 133,* 327-336. https://doi.org/10.1016/j.jbusres.2021.04.035

60. Vanegas-Cantarero, M. M., Pennock, S., Bloise-Thomaz, T., Jeffrey, H., & Dickson, M. J. (2022). Beyond LCOE: A multi-criteria evaluation framework for offshore renewable energy projects. *Renewable and Sustainable Energy Reviews, 161,* Article 112307. https://doi.org/10.1016/j.rser.2022.112307

61. Vărzaru, A. A., & Bocean, C. G. (2024). Digital transformation and innovation: The influence of digital technologies on turnover from innovation activities and types of innovation. *Systems, 12*(9), Article 359. https://doi.org/10.3390/systems12090359

62. Veselica Celić, R. (2025). Innovation strategies and organizational competitiveness. *Dubrovnik International Economic Meeting (DIEM), 10*(1), 109-118. https://doi.org/10.17818/DIEM/2025/1.10

63. Vitus, O. C. (2025). Leveraging technology to drive innovation: A mixed-methods approach to enhancing organizational creativity and competitiveness. *Innovation and Technology Studies, 2*(1), 1-6. https://doi.org/10.61784/its3005

64. Wen, J., Okolo, C. V., Ugwuoke, I. C., & Kolani, K. (2022). Research on influencing factors of renewable energy, energy efficiency, on technological innovation: Does trade, investment and human capital development matter? *Energy Policy, 160,* Article 112718. https://doi.org/10.1016/j.enpol.2021.112718

65. Wrat, G., Bhola, M., & Prasad, R. (2025). Future directions in wind energy: Automation, robotic maintenance, and cutting-edge communication solutions. *Journal of Mobile Multimedia, 21*(3-4), 713-728. https://doi.org/10.13052/jmm1550-4646.213421

66. Yalçin, T., Paradell Solà, P., Stefanidou-Voziki, P., Domínguez-García, J. L., & Demirdelen, T. (2023). Exploiting digitalization of solar PV plants using machine learning: Digital twin concept for operation. *Energies, 16*(13), Article 5044. https://doi.org/10.3390/en16135044

67. Yi, J., Dai, S., Li, L., & Cheng, J. (2024). How does digital economy development affect renewable energy innovation? *Renewable and Sustainable Energy Reviews, 192,* Article 114221. https://doi.org/10.1016/j.rser.2023.114221

APPENDIX A

Table A1. List of officially licensed renewable energy companies and related entities included in the study

Activity Type	No.	Company / Entity
Wind Power Generation	1	Saudi Arabian Oil Company (Saudi Aramco)
	2	Saudi Electricity Company
	3	Dumat Al Jandal Wind Company
	4	Al-Ghat Wind Energy Company
	5	Waad Al-Shamal Wind Energy Company
	6	NEOM Energy and Water Company
Solar Power Generation	1	Taqnia Energy Company
	2	Shuaibah Energy Company
	3	Shuaibah II Electric Power Company
	4	Noor Al-Wadi Renewable Energy Company
	5	Nawar Renewable Energy Company
	6	Saad II Renewable Energy Company
	7	Ishaa Renewable Energy Company
	8	Noor South Jeddah Photovoltaic Energy Company
	9	Al-Rass Solar Energy Company
	10	Layla Solar Energy Company
	11	NEOM Green Hydrogen Company Ltd.
	12	Al-Ghazalah Energy Company
	13	South Rabigh Renewable Energy Company
	14	Sudair First Renewable Energy Company
	15	Sakaka Solar Energy Company
	16	Sanaa Taiba Renewable Energy Company
	17	Tanweer Power Company
	18	Nabaa Renewable Energy Company
	19	Buraq Renewable Energy Company
	20	Mowaih Renewable Energy Company
	21	GDF Haradh Energy Company
	22	Zahra Energy Company
	23	Al-Aqqad Water Treatment Company – Tabuk 2 Wastewater Treatment Plant
	24	National Water Company – Ajyal Plant
	25	National Water Company – Hīt Plant
	26	Rawabi Desalination Company – Rabigh 4
	27	Maersk Saudi Arabia Logistics Services Company
	28	King Saud University – Medical City
	29	Jazlah Desalination Company
	30	Shuaibah III Desalination Company
	31	Saudi Water Authority – Jubail Solar Power Plant
	32	Reem Rabigh Energy Company
	33	Ministry of Defense
	34	NEOM Energy and Water Company
	35	Princess Nourah bint Abdulrahman University
	36	Imam Mohammad Ibn Saud Islamic University
	37	Cold Sky Energy Company
	38	Taibah University
	39	Nyar Global Renewable Energy Company

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