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Data-Driven Decision Making and Sustainable Innovation Performance: The Roles of Organizational Learning Capability and Sustainability-Oriented Leadership

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Abstract

Despite growing recognition of the strategic value of data-driven decision making (DDM) in contemporary organizations, the mechanisms and boundary conditions through which DDM is associated with sustainable innovation performance (SIP) remain theoretically underexplored. Drawing on Dynamic Capabilities Theory, Organizational Learning Theory, and the Sustainability Leadership Perspective, this study develops and tests a moderated mediation model in which organizational learning capability (OLC) mediates the DDM–SIP relationship and sustainability-oriented leadership (SOL) moderates both the DDM–OLC relationship and the indirect DDM–OLC–SIP path. Survey data were collected from 384 employees of 29 oil and gas companies in Libya and analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4. The results show that data-driven decision making is positively associated with both sustainable innovation performance and organizational learning capability, and that organizational learning capability is strongly associated with sustainable innovation performance. Organizational learning capability partially mediates the relationship between data-driven decision making and sustainable innovation performance, transmitting about half of the total effect. Furthermore, sustainability-oriented leadership positively moderates the relationship between data-driven decision making and organizational learning capability, and the indirect association between data-driven decision making and sustainable innovation performance through organizational learning capability is more than twice as strong when sustainability-oriented leadership is high as when it is low. These findings advance understanding of how data-driven practices are linked to sustainable innovation through organizational learning processes, and of the leadership conditions under which this pathway is stronger, with practical implications for strategic leadership, organizational transformation, and sustainable innovation management in complex and institutionally challenging emerging economy contexts.

Keywords: data-driven decision making; organizational learning capability; sustainability-oriented leadership; sustainable innovation performance; organizational transformation; dynamic capabilities; complex environments; emerging economies

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1. Introduction

The accelerating integration of digital technologies into organizational processes has fundamentally transformed how firms generate, process, and leverage information to

support strategic decisions. Among these transformations, data-driven decision making (DDM) has emerged as a critical organizational capability, enabling firms to substitute intuition-based managerial judgments with systematic, evidence-based analytical processes [1–3]. DDM is conceptualized in this study as a dynamic capability in the sense of Teece et al. [4] and Teece [5]: a higher-order organizational process through which firms sense sustainability-relevant information signals, seize innovation opportunities identified through data analysis, and reconfigure knowledge resources toward strategic sustainability goals. This dynamic capability framing distinguishes DDM from a simple information-processing routine by emphasizing its role in organizational adaptation and reconfiguration under environmental uncertainty, consistent with Shamim et al. [6], who treat big data decision-making capability from a dynamic capabilities view, and Goraya et al. [7], who frame DDM within the sensing, seizing, and reconfiguring logic of dynamic capability theory. In parallel, the global intensification of sustainability imperatives has elevated sustainable innovation performance (SIP) as a strategic priority across industries, compelling organizations to innovate not only for economic returns but also for social and environmental value creation [8–10]. Despite growing scholarly attention to both phenomena independently, the mechanisms through which data-driven decision making is associated with superior sustainable innovation outcomes remain theoretically underdeveloped and empirically underexplored, particularly in resource-rich economies characterized by institutional complexity and environmental uncertainty.

The oil and gas sector in Libya represents a compelling and theoretically generative empirical context for investigating these relationships. As one of the most hydrocarbon-dependent economies in the world, Libya relies on hydrocarbons for between 85 and 96 percent of government revenue [11]. Yet, Libyan oil and gas organizations operate under conditions of profound institutional instability, geopolitical uncertainty, regulatory fragmentation, and infrastructural deficits that have persisted since the political transitions following 2011 [12,13]. Libya's AI talent readiness score of 11.30 further points to a critical gap in the professional skills required for analytical decision making [11]. Within this hostile environment, the adoption of data-driven decision making represents both a strategic imperative and an organizational challenge, as firms must simultaneously develop analytical capabilities and sustain innovation performance under conditions of resource scarcity and governance uncertainty [14]. Evidence from Libya's conflict-affected oil sector also shows that relationships between organizational resources and performance can operate differently when institutional stability is compromised [15]. This context amplifies the theoretical relevance of understanding how DDM capabilities interact with organizational learning processes and leadership orientations in relation to sustainable innovation outcomes.

Existing literature has established evidence that DDM is associated with operational efficiency, competitive advantage, and organizational performance [7,16]. Similarly, a growing body of research has documented the positive associations between organizational learning capability (OLC) and innovation performance, confirming that organizations that effectively acquire, transfer, and integrate knowledge are better positioned to innovate sustainably [17–20], and organizational learning has been shown to transmit the performance value of AI-enabled dynamic capabilities [21]. However, the literature has not adequately theorized how DDM is associated with sustainable innovation performance, specifically whether this association is direct or is mediated through the organization's learning processes. Furthermore, while sustainability-oriented leadership (SOL) has been identified as a factor associated with sustainability outcomes [20,22,23], its boundary-setting role in moderating how strongly DDM is reflected in learning capability and ultimately in sustainable innovation has received scant empirical attention.

This study addresses these theoretical and empirical gaps by developing and testing a moderated mediation model in which organizational learning capability mediates the relationship between data-driven decision making and sustainable innovation performance, and sustainability-oriented leadership moderates both the relationship between DDM and OLC and the full indirect path from DDM through OLC to SIP. Three theoretical perspectives are integrated into a unified explanatory architecture rather than applied in parallel. Dynamic Capabilities Theory [4,5] provides the primary explanatory framework, positioning DDM as the sensing and seizing capability at the start of the innovation chain. Organizational Learning Theory [24,25] supplies the mediating mechanism, explaining how DDM sensing is converted into sustainable innovation performance through the knowledge acquisition, dissemination, and application processes that constitute organizational learning capability. The Sustainability Leadership Perspective [23,26] provides the boundary condition logic, specifying the leadership conditions under which the DDM-OLC conversion, and therefore the indirect DDM-OLC-SIP path, is amplified or attenuated. Upper Echelons Theory [27] and transformational leadership theory [28] are drawn upon as supporting perspectives that clarify the mechanisms through which sustainability-oriented leaders shape the organizational context, but they do not constitute additional primary theoretical foundations of the model. The integration of these perspectives enables this study to answer not only whether DDM is associated with sustainable innovation performance but how (through organizational learning) and under what leadership conditions (high versus low sustainability-oriented leadership) this association is strongest.

This study responds directly to calls for research examining how strategic leadership behaviors, organizational capabilities, and data-driven practices enable organizations to innovate for sustainability under conditions of institutional uncertainty and environmental complexity [14]. While prior research has examined strategic leadership and sustainable innovation largely as separate streams, there remains limited understanding of how leadership orientation interacts with organizational learning capability to strengthen the association between data-driven decision making and sustainable innovation in complex emerging economy environments. The theoretical novelty of this study should be stated precisely, because several of its component relationships have been examined before. Prior work has shown that the performance value of AI-enabled and data-related capabilities is transmitted through data-driven culture and organizational learning [21], that business analytics capability and organizational agility are antecedents of DDM [7], that big data decision-making capability can be understood from a dynamic capabilities view [6], that digital transformation is associated with sustainable innovation performance, with digital technology–business alignment and environmental uncertainty shaping this association [29], and that sustainability-oriented leadership is associated with learning and knowledge management processes [20,22]. Against this background, the contribution of the present study does not lie in new bivariate relationships but in combining these strands in a way that prior studies have not. First, it extends the learning-mediated logic from financial or general firm performance to sustainable innovation performance. Second, whereas prior studies treat leadership as an antecedent of learning, the present model treats sustainability-oriented leadership as a condition on how strongly a different capability, DDM, is associated with learning, and tests whether this condition carries through to the indirect association between DDM and SIP. Third, it examines this configuration in an institutionally complex resource sector where such evidence is absent; recent studies in Libya's oil and gas sector have examined other questions, such as employee performance and international competitiveness [15,30]. Because the data are cross-sectional and perceptual, the model specifies a theorized mechanism and boundary condition, and the empirical analysis tests whether the observed pattern of associations is consistent with them rather

than establishing the mechanism directly. By integrating Dynamic Capabilities Theory, Organizational Learning Theory, and the Sustainability Leadership Perspective into a unified moderated mediation framework, this study advances both scholarly understanding and practical guidance on how leaders can direct organizational capabilities toward sustainable innovation value creation in challenging institutional contexts.

The study makes several contributions to the literature. First, it extends Dynamic Capabilities Theory by positioning DDM as a sensing and seizing capability [5] whose association with sustainable innovation performance operates through learning-mediated transformation processes, extending evidence that the performance value of data-related capabilities depends on organizational learning [21,31] to sustainability outcomes. Second, it advances the organizational learning literature by providing evidence consistent with OLC operating as a mechanism linking analytical decision-making practices to sustainable innovation outcomes in an under-researched sector, extending the foundational OLC work of Jerez-Gomez et al. [17] to the specific institutional and sectoral conditions of Libya's oil and gas industry. Third, it contributes to the sustainability leadership literature by showing that the association between DDM and OLC and the indirect association between DDM and SIP are stronger at higher levels of SOL, which is consistent with SOL functioning as an important boundary condition of the DDM-OLC-SIP pathway, building on the leadership–learning link reported by Iqbal and Ahmad [20] and the association between sustainability-oriented leadership and knowledge management processes reported by Nguyen [22]. Fourth, the study provides empirically grounded insights for managers and policymakers in Libya's oil and gas sector, where evidence-based guidance for capability-building under institutional uncertainty is urgently needed [11]. Fifth, the study advances the moderated mediation literature in emerging economy resource sectors by specifying and empirically testing a first-stage moderated mediation model in which the conditional indirect effect of DDM on SIP through OLC varies significantly as a function of SOL level, responding to evidence that organizational relationships may operate differently in conflict-affected, resource-scarce environments [14,15].

The remainder of this paper is organized as follows: Section 2 presents the theoretical foundations and develops the research hypotheses. Section 3 describes the research methodology, including the sample, measurement instruments, and analytical strategy. Section 4 reports the results of the structural equation modeling analysis conducted using SmartPLS 4. Section 5 discusses the findings in light of the theoretical framework and prior empirical evidence. Section 6 presents the theoretical and practical implications, limitations, and directions for future research, and Section 7 concludes the study by summarizing its main findings.

2. Literature Review and Hypothesis Development

2.1. Theoretical Frameworks

The theoretical architecture of this study integrates three complementary theoretical perspectives: Dynamic Capabilities Theory as the primary explanatory framework, Organizational Learning Theory as the mediating mechanism theory, and the Sustainability Leadership Perspective as the boundary condition theory. Following recent calls for integrative rather than additive theorizing, in which each perspective is assigned a distinct explanatory role within one framework rather than placed side by side [32], the three perspectives are connected here through a single logic. Dynamic Capabilities Theory specifies what DDM is, namely a sensing and seizing capability, but it also implies that sensing alone is insufficient: value depends on reconfiguration, and reconfiguration rests on deliberate learning mechanisms [5,33]. Organizational Learning Theory specifies this reconfiguration mechanism, explaining how data-based insights become shared knowledge

and changed routines through organizational learning capability. The Sustainability Leadership Perspective then specifies direction. Dynamic capabilities and learning processes are, in themselves, neutral with respect to sustainability, and their contribution to sustainability outcomes depends on how central sustainability is to the firm's strategic orientation [34]. Sustainability-oriented leadership supplies this orientation and therefore conditions the extent to which data-derived learning is channeled toward sustainable innovation.

Taken together, these frameworks provide a coherent explanation of how and when data-driven decision making is associated with sustainable innovation performance. The specific theoretical insight of the moderated mediation model is that the sustainability value of DDM is neither automatic nor purely technical. It is learning-contingent, because it is transmitted through organizational learning capability, and it is leadership-contingent, because sustainability-oriented leadership conditions the first stage of this process, where data are converted into learning. None of the three perspectives alone yields this proposition. Dynamic Capabilities Theory alone treats DDM as valuable without specifying the mechanism or the direction of reconfiguration; Organizational Learning Theory alone explains learning without explaining its sustainability orientation; and the leadership perspective alone explains orientation without explaining how analytical capability is converted into innovation. Empirical work linking sustainable leadership to organizational learning and to dynamic capabilities in the pursuit of sustainable performance supports the plausibility of this integration [20,35].

2.1.1. Dynamic Capabilities Theory

Dynamic Capabilities Theory (DCT), originally articulated by Teece et al. [4] and subsequently elaborated by Teece [5], Eisenhardt and Martin [36], and Winter [37], provides the overarching explanatory framework for this study. DCT holds that sustainable competitive advantage in dynamic environments is not derived from the mere possession of resources but from the firm's capacity to sense, seize, and reconfigure those resources in response to changing environmental conditions [5,38]. Dynamic capabilities are defined as the higher-order organizational routines and processes through which firms integrate, build, and reconfigure internal and external competencies to address rapidly shifting environments [4,31].

In the context of this study, DDM constitutes a sensing and seizing capability. By systematically converting environmental data into actionable organizational intelligence, DDM enables firms to detect opportunities and threats, reconfigure knowledge resources, and direct innovation investment toward sustainability goals [1,39]. Analytics-based approaches that combine causal inference with predictive modeling, for example, allow firms to anticipate operational risks before they materialize and to act proactively rather than reactively [40], which reflects the essence of sensing in Teece's [5] framework.

Because DDM could alternatively be viewed as an organizational practice, an information-processing routine, or an analytical capability, its classification as a dynamic capability requires justification, and three arguments support it. First, dynamic capabilities are higher-order routines that change the firm's resource base, distinct from ordinary, or zero-level, capabilities that allow the firm to operate in the present [33,37]. An analytical capability, such as data infrastructure or business analytics skills, is an ordinary resource. DDM, as conceptualized in this study, is the patterned organizational routine of using analytical outputs to revise strategic and operational decisions and, through those decisions, to reallocate and recombine resources. This distinction is supported empirically by Goraya et al. [7], who show that business analytics capability and organizational agility are antecedents of DDM rather than equivalent to it, and who frame DDM within the sensing, seizing, and reconfiguring logic of dynamic capability theory. Second, Eisenhardt

and Martin [36] explicitly identify strategic decision-making processes, in which managers pool information and expertise to make choices that reshape the firm's resources, as a canonical dynamic capability; DDM is the evidence-based form of this process. Third, systematic reviews of dynamic capabilities for sustainability classify sustainability-related scanning, interpretive, and learning activities as microfoundations of sensing [34], and big data capability has been studied as a capability through which firms recognize and respond to sustainability demands [10]. DDM therefore differs from a mere information-processing routine because it is repeated, organization-wide, and directed at changing what the firm does, rather than at processing information for its own sake.

The dynamic capabilities perspective further implies that DDM contributes to sustainable innovation value not as a static resource but as an organizationally embedded process that supports learning, adaptation, and reconfiguration capacity. This positions organizational learning capability as the mechanism through which DDM sensing is converted into sustainable innovation performance, consistent with the DCT emphasis on reconfiguration as the pathway from sensing to value creation [5,33].

2.1.2. Organizational Learning Theory

Organizational Learning Theory (OLT), drawing on foundational contributions by Senge [25], Argyris and Schon [41], Huber [42], and Nonaka and Takeuchi [43], provides the mediating mechanism framework for this study. OLT posits that organizations that systematically acquire, disseminate, and apply knowledge from internal and external sources develop superior adaptive capacity and innovation capability [24]. Organizational learning capability, operationalized by Jerez-Gomez et al. [17] as a multidimensional construct encompassing managerial commitment, systems perspective, openness and experimentation, and knowledge transfer and integration, captures the organizational processes through which data-driven insights are transformed into shared knowledge routines and innovation behaviors.

Within the proposed model, OLT explains how DDM is linked to sustainable innovation performance. Data and analytics alone do not constitute innovation; rather, they must be absorbed, interpreted, and institutionalized through organizational learning processes before they can redirect organizational behavior toward sustainable innovation outcomes [10,17]. Wang et al. [10] make this argument explicit for sustainability, describing the cultivation of sustainability-oriented innovation as a continuous and deliberate organizational learning process based on knowledge flow. OLT thus supplies the process logic connecting DDM to SIP, specifying that the learning organization serves as the vehicle through which data-driven insights are translated into sustainable innovation action. On this point, the two theories are complementary rather than parallel: within the dynamic capability view, organizational learning capability is treated as a capability that links knowledge inputs to innovation outcomes [44], and deliberate learning is regarded as the mechanism from which dynamic capabilities themselves evolve [33].

2.1.3. Sustainability Leadership Perspective

The Sustainability Leadership Perspective [23,26] provides the boundary condition framework for this study. Sustainability-oriented leadership is characterized by the consistent embodiment of social, environmental, and ethical responsibility in leadership decision making, communication, and organizational culture building [20]. It takes a holistic approach that seeks long-term, balanced outcomes across economic, social, and ecological dimensions [45,46], and it belongs to a broader family of leadership approaches oriented toward sustainability, including sustainable, sustainability, and environmental leadership, which share an emphasis on directing organizations toward sustainability perfor-

mance [47,48]. The sustainability leadership perspective holds that leaders shape the normative, cognitive, and motivational context within which organizational capabilities are deployed. Two established theories inform this view, but they are not additional foundations of the model. Upper echelons theory [27] helps explain why leaders' values are reflected in organizational priorities and knowledge processes [22,49], and transformational leadership theory [28] helps explain how leaders motivate followers toward collective goals. Both are used only as supporting perspectives that clarify the behavioral mechanisms of SOL; the theoretical foundations of the model remain Dynamic Capabilities Theory, Organizational Learning Theory, and the Sustainability Leadership Perspective.

In the context of this study, sustainability-oriented leadership functions as a moderating boundary condition that strengthens or weakens the association between DDM and organizational learning capability and, through it, the indirect association between DDM and sustainable innovation performance. The need for such a boundary condition is underlined by evidence that data- and AI-intensive technologies do not automatically yield environmental gains: at the macro-level, AI robotics and supply chain integration have been associated with a rising rather than a falling ecological footprint [50]. What matters is the orientation under which such capabilities are deployed. When leaders actively communicate sustainability values, reward sustainability-oriented learning behaviors, and model sustainability-driven decision making, the organizational context becomes more receptive to the learning and innovation demands associated with DDM [20,22]. This establishes the theoretical rationale for hypothesizing that SOL amplifies the DDM-OLC relationship and the DDM-OLC-SIP indirect path.

2.2. Data-Driven Decision Making and Sustainable Innovation Performance

Data-driven decision making refers to the organizational practice of basing strategic and operational decisions on systematically collected, analyzed, and interpreted data rather than on intuition or experience alone [1,16]. Firms that successfully embed DDM practices develop a superior capacity to identify market trends, optimize resource allocation, detect innovation opportunities, and monitor the sustainability impacts of their activities [10,39].

Sustainable innovation performance encompasses the outcomes of innovation activities that simultaneously deliver economic value, address social needs, and reduce environmental impacts [9,10,51]. This tripartite conceptualization reflects the triple-bottom-line framework [52], in which organizational success is evaluated not only by financial returns but also by social and environmental contributions. Consistent with this framework, recent studies measure sustainable innovation performance across economic, social, and environmental dimensions [9,10], and evidence from Malaysian industries shows that green innovations are associated with environmental, social, and financial performance, with environmental and financial performance positively related to one another [53]. The three dimensions are therefore treated as related facets of a common capacity for sustainable innovation; the specification of SIP as a higher-order construct is justified in Section 3. The capacity to achieve sustainable innovation outcomes requires the ability to systematically monitor performance across economic, social, and environmental dimensions, which is precisely the analytical capacity that DDM enables.

From a dynamic capabilities perspective, DDM represents the sensing and seizing mechanism through which organizations detect sustainability-relevant data signals and direct innovation activities accordingly [5]. Firms with superior DDM capabilities can more accurately identify sustainability gaps, track regulatory and stakeholder expectations regarding sustainable performance, and allocate innovation resources to maximize sustainable value creation [34,39,54]. Recent empirical evidence supports this reasoning: Goraya et al. [7] find that DDM is positively associated with organizational performance in a hostile

environment, based on a survey of 309 respondents, with business analytics capability and organizational agility acting as prerequisites for this association; Wang et al. [10], in a multi-source study of 358 Chinese firms, find that big data capability is positively associated with sustainability-oriented innovation performance ($\beta = 0.241$, $p < 0.01$); and Cheng et al. [9] show, using fuzzy-set qualitative comparative analysis of 94 Chinese high-tech manufacturing firms, that particular configurations of digital technology adoption are associated with high sustainable innovation performance.

In the context of Libya's oil and gas sector, where organizations face intense environmental scrutiny, regulatory demands related to hydrocarbon governance, and community sustainability expectations, DDM provides the informational infrastructure necessary to monitor and improve sustainable innovation outcomes [30,55]. The hostile-environment evidence reported by Goraya et al. [7] is particularly relevant here, given the institutional instability and regulatory fragmentation that characterize the Libyan sector. Firms that leverage data analytics to track emissions, social impacts, and financial sustainability performance are better positioned to direct innovation investment toward high-sustainability-return activities. On the basis of this theoretical reasoning and empirical evidence, the following hypothesis is proposed:

H1. *Data-driven decision making is positively associated with sustainable innovation performance.*

2.3. Data-Driven Decision Making and Organizational Learning Capability

Organizational learning capability is defined as the organizational aptitude to systematically acquire, interpret, transfer, and integrate knowledge in ways reflected in lasting behavioral and structural changes that enhance organizational performance [17,56]. It encompasses the organizational systems, processes, and cultural orientations that enable firms to learn continuously from internal experiences and external environments. Jerez-Gomez et al. [17] operationalize OLC through four dimensions: managerial commitment to learning, a systems perspective, openness and experimentation, and knowledge transfer and integration.

Data-driven decision making is theorized to be a significant antecedent of organizational learning capability for several interrelated reasons. First, DDM fosters a culture of systematic evidence examination that is structurally compatible with the experimental and reflective orientation characteristic of learning organizations [1,25]. When organizations habitually rely on data to inform decisions, they institutionalize the practice of evidence-based inquiry, which in turn promotes openness to new information, experimentation with new practices, and critical reflection on existing routines, which are all hallmarks of high organizational learning capability [41,42].

Second, DDM systems accumulate organizational memory artifacts, such as databases, performance dashboards, and analytical reports, that serve as repositories for organizational knowledge [24,57]. The accumulation and systematic use of these artifacts strengthens knowledge transfer and integration processes, one of the four dimensions of OLC identified by Jerez-Gomez et al. [17]. In this way, DDM infrastructure directly supports the knowledge codification and dissemination processes through which organizational learning capability is built and sustained.

Third, organizations that invest in DDM capabilities tend to also invest in the human capital, systems, and cross-functional communication structures required to make sense of data outputs [58–60]. These structural investments reinforce the systems perspective and inter-unit coordination dimensions of OLC, as employees across departments must collaborate to develop and act on analytical insights. Goraya et al. [7] similarly conceptualize DDM as combining decision automation with collective sense-making among managers, a shared interpretive process that corresponds closely to the systems perspective and knowledge

integration dimensions of OLC. Recent empirical evidence is consistent with this reasoning. Drawing on organizational learning theory, Wang et al. [10] find that big data capability is strongly and positively associated with intellectual capital ($\beta = 0.733$, $p < 0.001$), that is, with the human, structural, and relational knowledge stocks that are built and drawn upon through organizational learning, a construct conceptually adjacent to OLC. The following hypothesis is therefore proposed:

H2. *Data-driven decision making is positively associated with organizational learning capability.*

2.4. Organizational Learning Capability and Sustainable Innovation Performance

The relationship between organizational learning capability and innovation performance is among the most extensively theorized and empirically examined relationships in the strategic management and organizational behavior literature. Learning organizations, that is, organizations that systematically develop the capacity to acquire, disseminate, and apply new knowledge, are consistently shown to exhibit superior innovation outcomes across technological, process, product, and sustainability innovation dimensions [56,61,62].

The mechanisms through which OLC is associated with sustainable innovation performance are multi-dimensional. First, managerial commitment to learning, a core dimension of OLC [17], ensures that organizational leadership actively supports the allocation of resources, time, and attention to learning activities that build sustainability-relevant innovation knowledge. When top managers signal that learning and knowledge development are strategic priorities, employees are more likely to engage in the knowledge exploration and sharing behaviors that enable sustainable innovation [17,56].

Second, openness and experimentation, another dimension of OLC, enables organizations to explore novel approaches to sustainability challenges, benchmark against external sustainability innovation practices, and integrate diverse knowledge sources into innovation routines [17,61]. Organizations with high openness and experimentation are better able to prototype and refine sustainable technologies, processes, and business models, which is reflected in superior environmental, social, and economic innovation performance.

Third, knowledge transfer and integration, defined as the extent to which knowledge is effectively shared across organizational units and embedded in organizational routines, ensures that sustainability insights generated in one part of the organization are efficiently disseminated and leveraged in others [43,63]. This systemic knowledge diffusion is theorized to amplify sustainable innovation performance by ensuring that sustainability-relevant learning is not localized in isolated departments but becomes an organization-wide resource.

Empirical evidence from Alegre and Chiva [61] in the ceramics industry; Alegre and Chiva [18] among Italian and Spanish ceramic tile producers; Migdadi [19] in the Jordanian banking, telecommunication, and healthcare sectors; Gomes et al. [64] among 159 Brazilian architecture and urbanism firms; and Camps and Luna-Arocas [62] indicates that higher OLC is consistently associated with superior innovation outcomes. Evidence from the sustainability domain points in the same direction. Iqbal and Ahmad [20], in a study of 369 SMEs in Pakistan, find that organizational learning is strongly associated with sustainable performance ($\beta = 0.625$, $p < 0.05$), and Wang et al. [10] find that intellectual capital, a knowledge-based construct grounded in organizational learning theory, is strongly associated with sustainability-oriented innovation performance ($\beta = 0.579$, $p < 0.001$). The following hypothesis is therefore proposed:

H3. *Organizational learning capabilities is positively associated with sustainable innovation performance.*

2.5. The Mediating Role of Organizational Learning Capability

Although H1 hypothesizes a direct relationship between DDM and SIP, the theoretical framework implies that this relationship is substantially explained by the mediating pathway through organizational learning capability. Mediation through OLC is theoretically coherent within both OLT and DCT: data-driven decision making establishes the informational and structural conditions that build learning capability, which in turn redirects organizational behavior toward sustainable innovation outcomes [5,24,25].

The mediation logic proceeds in two stages. In the first stage, DDM practices build organizational learning capability by embedding evidence-based inquiry into organizational routines, creating shared knowledge repositories, and fostering cross-functional data literacy [1,7]. In the second stage, organizational learning capability translates this accumulated analytical and knowledge capacity into sustainable innovation performance by enabling firms to systematically apply knowledge insights to the development of economically, socially, and environmentally sustainable innovations [17,51].

Importantly, this mediated pathway captures the process through which DDM is linked to innovation value, not merely by improving informational quality but by transforming the organizational learning system through which information becomes innovation. Without the development of organizational learning capability, DDM investments may remain as underexploited informational assets rather than contributors to sustainable innovation [39,60]. Several studies report mediation patterns consistent with this pathway. Wang et al. [10] find that the association between big data capability and sustainability-oriented innovation performance is mediated by intellectual capital, a knowledge-based mechanism grounded in organizational learning theory. Organizational learning capability has also been found to act as an intermediate mechanism between strategic orientations and innovation-related outcomes: linking entrepreneurial orientation to innovation performance and firm performance among European ceramic tile producers [18], linking entrepreneurial orientation to innovation capability among Algerian firms [44], and linking entrepreneurial orientation to organizational performance in knowledge-intensive service firms [64]. Similarly, organizational learning mediates the relationship between business model design and innovation performance [65]. At the leadership level, Iqbal and Ahmad [20] report that organizational learning partially mediates the relationship between sustainable leadership and sustainable performance (indirect effect $\beta = 0.307$, $p = 0.016$). Together, these findings suggest that organizational learning capability is a recurrent channel through which organizational capabilities and orientations are associated with innovation and sustainability outcomes. The following hypothesis is therefore proposed:

H4. *Organizational learning capability mediates the relationship between data-driven decision making and sustainable innovation performance.*

2.6. The Moderating Role of Sustainability-Oriented Leadership

Sustainability-oriented leadership refers to the consistent demonstration of social, environmental, and ethical responsibility in leaders' decisions, communications, and organizational culture-building activities [20,23,45]. Drawing on the sustainability leadership perspective [26], and using transformational leadership theory [28] only as a supporting lens on how leaders motivate followers, SOL is conceptualized as a leadership orientation that articulates sustainability as a core organizational value, models sustainability-driven behavior, and establishes the motivational and normative context that enables organizational members to direct their learning and innovation activities toward sustainability goals [66]. Recent reviews of leadership in the context of corporate sustainability emphasize this role

of leaders in supporting organizational change, innovation, and sustainability-oriented outcomes [47,48,67].

The first moderating hypothesis (H5) concerns the relationship between DDM and OLC. While DDM establishes the informational conditions for organizational learning, the extent to which these informational conditions are converted into learning capability is theorized to depend on the organizational climate established by sustainability-oriented leadership. Leaders who consistently communicate the importance of sustainability, reward sustainability-oriented learning, and model the systematic use of evidence in sustainability decision making amplify the receptiveness of the organizational learning system to DDM inputs [20,22]. Conversely, when sustainability-oriented leadership is weak or absent, DDM investments may expand data capacity without fostering sustainability-oriented learning, as employees lack the motivational and normative context to channel data insights toward sustainability knowledge development.

This argument is further supported by upper echelons theory [27], used here as a supporting perspective, which holds that leaders' values and orientations shape organizational resource allocation, cultural norms, and strategic priorities. Sustainability-oriented leaders cultivate an organizational environment in which data-driven insights are interpreted through a sustainability lens, sustainability-relevant knowledge is prioritized in organizational learning routines, and experimentation with sustainability innovations is encouraged and supported [20,26]. Recent empirical studies are consistent with this mechanism. Nguyen [22], drawing on upper echelons theory in a survey of 398 managers in Vietnamese service firms, finds that sustainability-oriented leadership is positively associated with knowledge creation, acquisition, sharing, and application; notably, the direct association between SOL and green innovation was not confirmed, which suggests that SOL operates through knowledge and learning processes rather than directly on innovation outcomes. Achmad and Wiratmadja [35] find that sustainable leadership is positively associated with both knowledge management and dynamic capabilities among 236 Indonesian SMEs, and Iqbal and Ahmad [20] report a positive association between sustainable leadership and organizational learning ($\beta = 0.490$, $p < 0.05$). In addition, Iqbal et al. [45] find that SOL is indirectly associated with employees' pro-environmental behavior through perceived procedural environmental justice, illustrating that SOL works by shaping the interpretive and normative context in which organizational initiatives are received. These findings suggest that SOL is most plausibly positioned at the first stage of the model, where it conditions the conversion of data-driven insights into organizational learning. The following hypothesis is therefore proposed:

H5. *Sustainability-oriented leadership positively moderates the relationship between data-driven decision making and organizational learning capability such that the relationship is stronger when sustainability-oriented leadership is high.*

The second moderating hypothesis (H6) extends the moderation logic to the full indirect effect of DDM on SIP through OLC. Moderated mediation theory [68,69] provides the statistical and theoretical basis for this hypothesis, which posits that the indirect effect of DDM on SIP via OLC is conditional on the level of sustainability-oriented leadership. Because SOL is modeled as a moderator of the first stage of the indirect path (DDM to OLC), the model is a first-stage moderated mediation model, and the conditionality of the indirect effect is assessed through the index of moderated mediation [70].

The theoretical rationale for H6 builds on both H5 and the sustainability leadership perspective: if SOL strengthens the conversion of DDM into OLC (H5), and if OLC is positively associated with SIP (H3), then the full indirect path from DDM through OLC to SIP should be stronger in contexts characterized by high sustainability-oriented leadership. This condi-

tional indirect effect reflects the theoretical argument that sustainability-oriented leadership amplifies the entire DDM–learning–innovation chain: by fostering a sustainability-oriented organizational climate, SOL helps ensure that data-driven learning processes are directed toward and culminate in sustainable innovation outcomes rather than narrowly economic or operational improvements [23,45].

This moderated mediation hypothesis is consistent with recent theoretical developments in the sustainability and leadership literature. Prior studies have established the components of this argument separately: sustainable leadership is associated with organizational learning, which in turn mediates its association with sustainable performance [20], and sustainable leadership is associated with the knowledge processes and dynamic capabilities on which sustainability outcomes depend [22,35,71]. These studies, however, position sustainable leadership as an antecedent of learning. The present study extends this work by theorizing SOL as a condition under which a distinct capability, DDM, is converted into learning, an interaction that, to the best of our knowledge, has not previously been tested. Avery and Bergsteiner [26] theorize that sustainability leadership fosters a systemic organizational orientation that amplifies the translation of organizational capabilities into long-term sustainable performance. The following hypothesis is therefore proposed:

H6. *Sustainability-oriented leadership moderates the indirect relationship between data-driven decision making and sustainable innovation performance through organizational learning capability such that the indirect effect is stronger when sustainability-oriented leadership is high.*

2.7. Research Model

Figure 1 presents the conceptual research model integrating the six hypotheses. The model depicts DDM as the independent variable with both a direct effect on SIP (H1) and an indirect effect through OLC (H2, H3, H4). Sustainability-oriented leadership moderates the first-stage relationship between DDM and OLC (H5) and the full indirect DDM-OLC-SIP path (H6). In this model, OLC is specified as a mediator and SOL as a moderator; SOL is not hypothesized to mediate any relationship. This moderated mediation architecture provides a theoretically grounded and empirically testable representation of the study's core propositions.

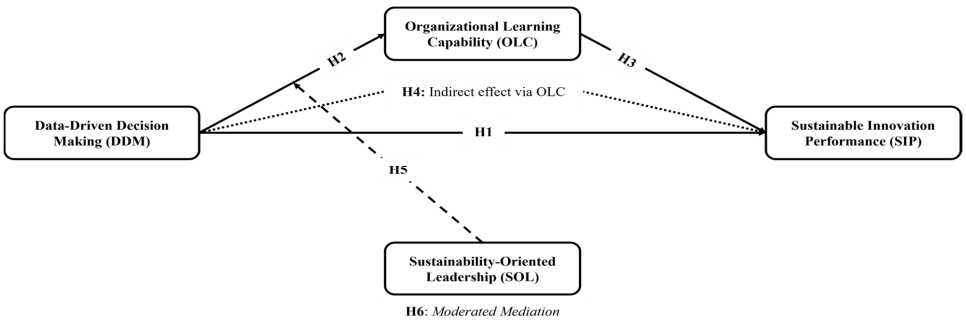


Figure 1. Conceptual research model. Note: Solid lines represent direct paths (H1–H3), the dotted line represents the indirect path from DDM to SIP through OLC (H4), and the dashed line represents the moderating effect of SOL on the relationship between DDM and OLC (H5). H6 denotes first-stage moderated mediation, in which SOL moderates the indirect relationship between DDM and SIP through OLC by conditioning the first stage (DDM → OLC) of the mediated path.

3. Methodology

3.1. Research Design, Sampling Strategy, and Data Collection

This study adopts a quantitative, cross-sectional survey research design to empirically test the proposed moderated mediation model in Libya's oil and gas sector. A quantita-

tive approach is appropriate because the research objective is to test theoretically derived hypotheses concerning the associations between data-driven decision making, organizational learning capability, sustainability-oriented leadership, and sustainable innovation performance. A cross-sectional design was chosen because it is well-suited to capturing perceptual data on organizational practices and performance at a single point in time, which is consistent with the epistemological assumptions underlying partial least squares structural equation modeling [72,73]. Because the data are cross-sectional, the hypothesized relationships are tested as associations, and the results do not permit causal inference.

Libya's oil and gas sector constitutes the empirical context for this investigation. As the strategic national industry and economic backbone of the country, the sector accounts for more than 90 percent of government revenues and exceeds 70 percent of gross domestic product, making it the most resource-intensive sector in the Libyan economy [74]. Importantly, Libyan oil and gas organizations operate under persistent conditions of institutional uncertainty, geopolitical complexity, and regulatory fragmentation that amplify the strategic importance of evidence-based decisions and sustainability-oriented innovation [12,13]. The sector is also characterized by rich data environments, including operational dashboards, maintenance records, real-time production monitoring, environmental indicators, and safety data, that make the adoption of data-driven decision making both feasible and strategically relevant [11]. At the same time, increasing national and international pressure regarding emissions, waste management, energy efficiency, community welfare, and occupational health and safety constitutes a strong institutional impetus for sustainable innovation. It is important to note that this study does not characterize Libya's oil and gas sector as fully digitally mature; rather, it is presented as a sector where data use and sustainability innovation are increasingly necessary due to operational, environmental, and strategic pressures.

Sampling frame and procedure. The sampling frame was drawn from the official registry of the National Oil Corporation of Libya and comprised 48 companies, including its subsidiaries, joint ventures, and oilfield service providers, which together employ an estimated 18,000 to 25,000 people. By activity type, the frame included 16 exploration and production companies, 8 refining and processing companies, 7 distribution and logistics companies, 10 oilfield service companies, and 7 energy support service companies. Because access to employees in the Libyan oil and gas sector is restricted and no employee-level sampling frame was available to the researchers, a non-probability purposive sampling procedure was adopted. The human resources department of each company was contacted to obtain permission and to facilitate distribution. In each company, the human resources department sent the survey link to 20 employees who were willing to participate and who held operational-level positions relevant to the study constructs, giving a total of 960 invitations (320 in exploration and production, 160 in refining and processing, 140 in distribution and logistics, 200 in oilfield services, and 140 in energy support services). Of the 48 companies, 32 agreed to participate and returned responses. Because the sample was not randomly drawn, the findings should be generalized to the wider sector with caution, as discussed in Section 6.3.

Target respondents included managers, engineers, supervisors, technical and operational staff, and IT, data, safety, or quality staff across multiple functional areas of oil and gas organizations, encompassing operations and production, engineering and maintenance, safety, health and environment, IT and data systems, and planning, administration, and quality. These respondent categories were selected because they possess sufficient awareness of organizational decision-making practices, learning processes, leadership behaviors, and sustainability performance outcomes to respond meaningfully to the constructs under investigation.

Data were collected through a structured online questionnaire administered through Google Forms between 20 April and 30 June 2026. Two reminders were sent at four-week intervals [75]. Participation was voluntary and anonymous, and informed consent was obtained from all participants before they completed the questionnaire. Data collection began after the study had been approved by the Institutional Review Board of Cyprus Health and Social Sciences University (Approval Code: KSTU/2025/109; Approval Date: 12 April 2026). Of the 960 questionnaires distributed, 429 responses were returned from the 32 participating companies, an initial return rate of 44.7 percent. Following systematic data screening, 45 responses were excluded based on three criteria: 19 questionnaires contained missing data exceeding 10 percent of the items; 15 responses exhibited careless answering patterns, identified through straight-lining and low response variance across items [76]; and 11 responses were identified as multivariate outliers using Mahalanobis distance in IBM SPSS version 25.0 Statistics [77,78]. Because all returned responses from three companies were removed under these criteria, no valid cases remained from these companies; no company was excluded as a whole on any other basis. The final valid sample therefore comprised 384 usable responses from 29 companies (mean = 13.24 respondents per company; SD = 2.34; median = 13; range = 10 to 18), yielding an effective response rate of 40.0 percent relative to the 960 questionnaires distributed, which is considered acceptable in organizational survey research [79,80]. Skewness values fell within ±1.8 and kurtosis values within ±3.5. Because PLS-SEM is a nonparametric method that does not require multivariate normality, these deviations do not affect the validity of the estimates [72].

Unit of analysis and nested data. The constructs examined in this study are defined at the organizational level, whereas the data were collected from individual employees. Consistent with the perceptual approach widely used in organizational capability research, respondents acted as informants who reported their perceptions of the practices, leadership, and performance of the organization in which they work [17,81]. The unit of observation is therefore the individual, and the results are interpreted as employees' perceptions of organizational characteristics rather than as objective organization-level measures. Because the 384 respondents were drawn from 29 companies, responses are nested within companies. Each respondent was assigned a company identification code. The degree of non-independence was assessed by estimating a random-intercept-only (null) linear mixed model for each construct with the SPSS MIXED procedure, using the unstandardized latent variable scores from the final SmartPLS estimation and the company identifier as the grouping variable; ICC(1) was computed as the ratio of between-company variance to total variance [82]. ICC(1) was 0.005 for OLC, 0.041 for SIP, 0.084 for DDM, and 0.091 for SOL, indicating negligible clustering in the mediator, low clustering in the outcome, and moderate clustering in the predictor and the moderator. Because company-level clustering is concentrated in the exogenous constructs rather than in the endogenous constructs, the data were analyzed at the individual level. The robustness of the structural results to the nested structure is assessed in Section 4.8, and its implications are acknowledged in Section 6.3.

Sample size and statistical power. The adequacy of the sample size was assessed with a model-specific power analysis. In PLS-SEM, the minimum sample size is determined by the largest number of structural paths pointing at any endogenous construct [72]. In the present model, OLC receives three such paths (DDM, SOL, and the DDM × SOL interaction term). An a priori power analysis for the F test in multiple regression, following the procedure implemented in G*Power 3.1 [83], indicated that a minimum of 77 cases is required to detect a medium effect ($f^2 = 0.15$) with three predictors at $\alpha = 0.05$ and a statistical power of 0.80, and 119 cases for a power of 0.95 [84]. Because interaction effects in organizational research are typically small [85], a post hoc power analysis was also performed for the

smallest observed effect in the model, the DDM × SOL interaction on OLC ($f^2 = 0.028$; see Section 4). With $N = 384$, the statistical power to detect this effect exceeded 0.90. The final sample of 384 valid responses therefore provides adequate power for the hypothesized model, which includes multiple latent variables, direct effects, mediation, moderation, and a conditional indirect effect. The sample size is also sufficient for bootstrapping with 5000 resamples, higher-order construct assessment, and predictive evaluation using PLSpredict, as recommended by Shmueli et al. [86].

3.2. Respondents' Profile

Table 1 presents the demographic profile of the 384 respondents. The majority of respondents were male (77.1%), reflecting the gender composition typically observed in the oil and gas sector in Libya and the broader Middle East and North Africa (MENA) region. In terms of age, the largest group fell within the 30–39 years category (38.5%), indicating a predominantly mid-career respondent profile. With respect to education, more than half of respondents held a bachelor's degree (55.7%), followed by those with a master's degree (22.7%), suggesting a technically qualified workforce capable of evaluating the constructs under investigation. Engineers represented the largest occupational category (30.5%), followed by technical and operational staff (21.4%) and supervisors (20.3%). Regarding work experience, the majority of respondents had between 5 and 15 years of industry experience (59.6% combined), indicating substantial exposure to organizational practices related to decision making, learning, leadership, and innovation. Operations and production was the most represented department (30.2%), followed by engineering and maintenance (24.5%). Exploration and production was the most common company activity type (34.4%). Overall, the respondent profile reflects a diverse, technically qualified, and experienced workforce appropriate for the constructs and research objectives of this study.

Table 1. Respondents' Demographics.

Demographic Variable	Category	Frequency	Percentage
Gender	Male	296	77.1%
	Female	88	22.9%
Age	Less than 30 years	67	17.4%
	30 to 39 years	148	38.5%
	40 to 49 years	106	27.6%
	50 years and above	63	16.4%
Education level	Diploma or below	61	15.9%
	Bachelor's degree	214	55.7%
	Master's degree	87	22.7%
	Doctorate or professional qualification	22	5.7%
Job position	Manager	51	13.3%
	Engineer	117	30.5%
	Supervisor	78	20.3%
	Technical or operational staff	82	21.4%
	IT, data, safety, or quality staff	56	14.6%
Work experience	Less than 5 years	58	15.1%
	5 to 10 years	128	33.3%
	11 to 15 years	101	26.3%
	More than 15 years	97	25.3%

Table 1. *Cont.*

Demographic Variable	Category	Frequency	Percentage
Department	Operations and production	116	30.2%
	Engineering and maintenance	94	24.5%
	Safety, health, and environment	67	17.4%
	IT and data systems	46	12.0%
	Planning, administration, and quality	61	15.9%
Company activity	Exploration and production	132	34.4%
	Refining and processing	78	20.3%
	Distribution and logistics	54	14.1%
	Oilfield services	76	19.8%
	Energy support services	44	11.5%

3.3. Measurement of Constructs

All constructs were measured using established scales from the prior literature, adapted to the context of Libya's oil and gas sector. Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was prepared in English and translated into Arabic, and the Arabic version was then translated back into English to verify semantic equivalence [87]. All scale items were reviewed by 25 experts, 10 academics in management, sustainability, and quantitative research methods and 15 industry professionals from the oil and gas sector, who assessed the relevance, clarity, and contextual fit of each item, prior to pilot testing. A pilot study with 30 employees, who were excluded from the main sample, confirmed the clarity and comprehensibility of the instrument; Cronbach's alpha exceeded 0.70 for all constructs [88], and minor wording changes were made to improve clarity. The full list of measurement items and their sources is provided in Appendix A (Table A1).

Data-driven decision making (DDM) was measured using six items adapted from Goraya et al. [7], who adapted them from Cao et al. [89], capturing the organization's reliance on data-based insights, real-time analytical decisions, and evidence-based responsiveness. A representative item is "[To what extent does your organization] use real-time data to make timely decisions?" Organizational learning capability (OLC) was measured using the full 16-item scale developed by Jerez-Gomez et al. [17], organized across four dimensions: managerial commitment (MC, five items), systems perspective (SP, three items), openness and experimentation (EX, four items), and knowledge transfer and integration (TR, four items). In SmartPLS 4, OLC was modeled as a reflective–reflective higher-order construct. A representative item is "This organization promotes experimentation and innovation as ways to improve work processes." Sustainability-oriented leadership (SOL) was measured using the 14-item scale adapted from Iqbal et al. [45] and Iqbal and Ahmad [20], capturing social, environmental, and ethical leadership dimensions, and modeled as a reflective first-order construct in SmartPLS 4. A representative item is "Organizational leadership acts in an environmentally responsible manner." Sustainable innovation performance (SIP) was measured using 14 items adapted from Cheng et al. [9], covering economic (ECP, four items), social (SOP, five items), and environmental innovation performance (ENP, five items), and modeled as a reflective–reflective higher-order construct. A representative item is "Our organization's sustainable innovation activities have reduced emissions."

Specification of the higher-order constructs. The choice between reflective and formative specification of the higher-order constructs was made on theoretical grounds [90]. Multidimensional constructs can be conceptualized either as superordinate (latent) constructs,

which exist at a deeper level than their dimensions and are manifested through them, or as aggregate constructs, which are formed as composites of their dimensions [91,92]. Jarvis et al. [93] propose four decision rules for this choice: the direction of causality between the construct and its dimensions, the interchangeability of the dimensions, the expected covariation among them, and whether the dimensions share the same antecedents and consequences. For OLC, Jerez-Gomez et al. [17] conceptualize managerial commitment, systems perspective, openness and experimentation, and knowledge transfer and integration as interrelated manifestations of a single underlying learning capability, which they validated as one multidimensional second-order construct; the dimensions are therefore expected to covary, and a change in the overall capability is expected to be reflected in all four dimensions. A reflective–reflective specification is consistent with this conceptualization. For SIP, we explicitly considered the alternative that the economic, social, and environmental dimensions could be regarded as complementary components that jointly form overall performance, which would imply a reflective–formative specification. This alternative was not adopted for three reasons. First, in terms of the direction of causality, SIP is conceptualized in this study as the organization's underlying capacity to achieve sustainable innovation outcomes, a superordinate construct that is expressed simultaneously in economic, social, and environmental results [91], rather than as an index computed from them. This view follows the integrative logic of the triple bottom line and of shared value creation, in which sustainable innovation is defined by the joint pursuit of the three forms of value rather than by trade-offs among them [94,95]. A formative specification would imply that the dimensions are compensatory so that a gain in economic innovation performance could offset a decline in environmental performance while overall SIP remained unchanged, an implication that is inconsistent with the construct as defined here. Second, in terms of covariation and shared antecedents, the dimensions are expected to move together because they draw on common organizational resources, such as knowledge, learning routines, and leadership attention [96–98], and are therefore expected to respond to the same antecedents in the model, DDM and OLC. This expectation is supported by evidence that environmental, social, and economic innovation outcomes are positively interrelated rather than traded off against one another [10,53], and it is consistent with Cheng et al. [9], from whom the measures were adapted and who assess sustainable innovation performance jointly across the three dimensions, and with Lin and Mao [29], who adopt the same specification of sustainable innovation performance. Third, the empirical results are consistent with the reflective specification: the three dimensions load strongly on SIP (ECP = 0.871, SOP = 0.887, ENP = 0.951), and the four dimensions load strongly on OLC (0.779 to 0.910), indicating that each dimension shares most of its variance with the higher-order construct [90]. Both higher-order constructs were estimated with the repeated indicators approach, which is appropriate for reflective–reflective specifications [90,99]. Because the specification of SIP nevertheless rests on a theoretical choice, this issue is also acknowledged in Section 6.3.

3.4. Procedural and Statistical Control of Common Method Variance

Given the cross-sectional design and the use of a single questionnaire in which all constructs were assessed through individual perceptual responses, the potential for common method variance (CMV) was addressed through both procedural and statistical remedies [81,100]. Procedural controls included assurance of respondent anonymity, emphasis on response confidentiality, clarification that no right or wrong answers existed, voluntary participation without evaluative consequences, clear and unambiguous item wording, and physical separation of construct sections within the questionnaire. Pilot testing was conducted to detect and eliminate ambiguous items prior to final distribution.

Statistical assessment of CMV was conducted using two approaches. First, Harman's single-factor test was applied in IBM SPSS Statistics, and the first extracted factor accounted for 38.8 percent of the total variance, remaining below the commonly applied 50 percent threshold [81,101]. Because Harman's test is a weak diagnostic that cannot by itself establish the absence of method bias [102], a second and more rigorous test was applied. Second, a construct-level full collinearity assessment was conducted following Kock [100]. Following the procedure described by Gaskin et al. [103], a covariance-based confirmatory factor model including all first-order constructs (DDM, MC, SP, EX, TR, SOL, ECP, SOP, and ENP) was estimated in SmartPLS 4, and the latent construct correlation matrix was extracted. The full collinearity VIF of each construct was then computed as the corresponding diagonal element of the inverse of this correlation matrix, which is equivalent to $1/(1 - R^2)$ when that construct is regressed on all other constructs. Because latent correlations from covariance-based estimation are corrected for measurement error, this procedure yields conservative VIF estimates. All full collinearity VIF values ranged between 1.636 (SOL) and 2.881 (ECP) (DDM = 1.645; MC = 2.365; SP = 1.890; EX = 1.799; TR = 2.377; SOL = 1.636; ECP = 2.881; SOP = 2.038; ENP = 2.029), below the recommended threshold of 3.3 [79,100], providing further evidence that common method bias does not substantially distort the structural estimates. These construct-level values are distinct from the indicator-level VIFs used to assess collinearity among measurement items (1.346 to 2.994), which are reported in Table 2. It is acknowledged that these procedures reduce but do not eliminate the risk of common method bias, particularly because all constructs, including the outcome variables, were reported by the same respondents in a single questionnaire (see Section 6.3), and future research employing longitudinal or multi-source designs would provide additional safeguards [81].

Table 2. Reliability and Convergent Validity Results.

Construct/Item	Loading	VIF	Cronbach's α	ρA	CR	AVE
DDM			0.958	0.959	0.966	0.826
DDM1	0.909	2.440				
DDM2	0.908	2.054				
DDM3	0.924	1.506				
DDM4	0.935	2.047				
DDM5	0.881	2.809				
DDM6	0.896	2.344				
OLC (HOC)			0.936	0.939	0.944	0.518
MC	0.910		0.917	0.918	0.938	0.752
MC1	0.875	2.393				
MC2	0.885	2.427				
MC3	0.869	2.798				
MC4	0.857	2.639				
MC5	0.831	2.394				
SP	0.839		0.839	0.847	0.903	0.756
SP1	0.901	2.384				
SP2	0.848	2.041				
SP3	0.859	1.783				
EX	0.854		0.826	0.854	0.885	0.697
EX1	0.887	2.514				
EX2	0.844	2.208				
EX3	0.860	2.051				

Table 2. *Cont.*

Construct/Item	Loading	VIF	Cronbach's α	ρA	CR	AVE
EX4	0.740	1.346				
TR	0.779		0.846	0.848	0.897	0.685
TR1	0.809	1.789				
TR2	0.795	1.770				
TR3	0.853	2.265				
TR4	0.851	2.266				
SOL			0.940	0.942	0.948	0.601
SOL1	0.728	2.498				
SOL2	0.780	2.584				
SOL3	0.733	2.994				
SOL4	0.723	2.040				
SOL5	0.721	2.132				
SOL6	0.794	2.454				
SOL7	0.725	2.099				
SOL8	0.840	2.938				
SOL9	0.824	2.504				
SOL10	0.731	1.942				
SOL11	0.847	1.971				
SOL12	0.825	2.700				
SOL13	0.724	1.978				
SOL14	0.834	2.698				
SIP (HOC)			0.936	0.938	0.944	0.549
ECP	0.871		0.889	0.891	0.923	0.751
ECP1	0.868	2.499				
ECP2	0.811	1.870				
ECP3	0.914	2.319				
ECP4	0.870	2.459				
SOP	0.887		0.890	0.890	0.919	0.694
SOP1	0.825	2.228				
SOP2	0.852	2.237				
SOP3	0.846	2.365				
SOP4	0.833	2.389				
SOP5	0.834	2.455				
ENP	0.951		0.828	0.833	0.880	0.609
ENP1	0.795	2.028				
ENP2	0.747	1.775				
ENP3	0.793	1.929				
ENP4	0.831	2.239				
ENP5	0.732	1.720				

Note. HOC = Higher-Order Construct; MC = Managerial Commitment; SP = Systems Perspective; EX = Openness and Experimentation; TR = Knowledge Transfer and Integration; ECP = Economic Innovation Performance; SOP = Social Innovation Performance; ENP = Environmental Innovation Performance; for the first-order components of OLC and SIP, the loading column reports the second-order loading on the respective HOC; CR = composite reliability (ρC); AVE = average variance extracted; VIF = variance inflation factor. All loadings significant at $p < 0.001$.

3.5. Analytical Strategy

Data preparation and descriptive analysis were conducted using IBM SPSS Statistics 27, including frequency analysis of demographic variables, data screening, and Harman's single-factor test for CMV assessment. Hypothesis testing was conducted using SmartPLS 4 [104], following the two-stage analytical procedure recommended by Hair et al. [79]. In the first stage, the measurement model was assessed for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. OLC and SIP were specified as reflective–reflective higher-order constructs and estimated with the repeated indicators approach, which is appropriate for reflective–reflective higher-order constructs because the higher-order construct is reflected in its lower-order components and its variance in the structural model is explained only by its antecedent constructs [90]. Both the lower-order and the higher-order measurement models were assessed.

In the second stage, the structural model was evaluated through collinearity diagnostics, direct hypothesis testing, mediation analysis, moderation analysis, and conditional indirect effect estimation for moderated mediation. Overall model fit was assessed using the standardized root mean square residual (SRMR), with values below 0.08 indicating acceptable fit [105,106]. Explanatory power was evaluated with R^2, and effect sizes with f^2 using Cohen's [84] thresholds for main effects and Kenny's [107] thresholds for interaction effects.

Predictive power was assessed using PLSpredict with 10 folds and 10 repetitions [86]. Q^2 predict values were examined at the construct level, and, at the indicator level, Q^2 predict, root mean square error (RMSE), and mean absolute error (MAE) were computed for the indicators of the key endogenous construct and compared against a naive linear regression model benchmark.

Mediation (H4) was assessed by estimating the direct, indirect, and total effects of DDM on SIP together with their bootstrapped confidence intervals; the type of mediation was determined from the significance of the indirect and direct effects [108,109]. Moderation (H5) was tested using the two-stage approach to interaction term generation in SmartPLS 4, in which the standardized latent variable scores of DDM and SOL are multiplied to form the interaction term, which is then entered as a predictor of OLC alongside the main effects of DDM and SOL [110]. The nature of the interaction was examined with simple slope analysis at low (−1 SD) and high (+1 SD) levels of SOL, and conditional effects of DDM on OLC were estimated at low, mean, and high levels of SOL. Moderated mediation (H6) was assessed by estimating the conditional indirect effects of DDM on SIP through OLC at low (−1 SD), mean, and high (+1 SD) levels of SOL and by testing the index of moderated mediation; moderated mediation is supported when the 95 percent confidence interval of the index excludes zero [70]. Differences between conditional indirect effects are interpreted on the basis of this index and its confidence interval rather than through qualitative labels.

All direct, indirect, total, and conditional indirect effects were estimated using bias-corrected bootstrapping with 5000 resamples and a 95 percent confidence interval [72,111]. Following common reporting practice, p-values below 0.001 are reported as $p < 0.001$. The robustness of the structural results to the nesting of respondents within companies was assessed with design effects and Moulton-corrected standard errors [112,113], as reported in Section 4.8.

4. Results and Data Analysis

4.1. Measurement Model Assessment

The measurement model was evaluated following the criteria established by Hair et al. [114], Fornell and Larcker [115], and Henseler et al. [116]. Assessment covered indicator reliability through outer loadings; internal consistency reliability through Cronbach's

alpha, ρA, and composite reliability (CR); convergent validity through average variance extracted (AVE); and discriminant validity through the heterotrait–monotrait ratio of correlations (HTMT). For OLC and SIP, which were modeled as reflective–reflective higher-order constructs (HOCs), both the first-order component models and the higher-order construct models were assessed, consistent with the repeated indicators approach recommended by Sarstedt et al. [90].

Table 2 presents the reliability and convergent validity results. All indicator outer loadings exceeded the recommended threshold of 0.708 [72], ranging from 0.721 (SOL5) to 0.935 (DDM4). At the higher-order level, the loadings of the first-order components on their HOCs ranged from 0.779 (TR) to 0.910 (MC) for OLC and from 0.871 (ECP) to 0.951 (ENP) for SIP, all significant at $p < 0.001$. Cronbach's alpha values ranged from 0.826 (EX) to 0.958 (DDM), all exceeding the 0.70 benchmark [88]. Composite reliability values ranged from 0.880 (ENP) to 0.966 (DDM), and ρA values ranged from 0.833 (ENP) to 0.959 (DDM), both confirming internal consistency reliability across all constructs. AVE values ranged from 0.518 (OLC HOC) to 0.826 (DDM), all exceeding the 0.50 threshold required for convergent validity [115]. Indicator VIF values ranged from 1.346 (EX4) to 2.994 (SOL3), below the threshold of 3.3, indicating no collinearity among indicators [79,100]. These results provide strong evidence for the reliability and convergent validity of all measurement instruments.

4.2. Discriminant Validity

Discriminant validity was assessed using the HTMT criterion, which is the most rigorous and recommended approach for PLS-SEM [116,117]. Tables 3 and 4 present the HTMT ratios for the first-order constructs and for the higher-order model, respectively. All HTMT values were below the conservative threshold of 0.85 [116] and below the more lenient 0.90 criterion [79]. Among the first-order constructs, values ranged from 0.478 (SOP–SP) to 0.790 (SOL–SOP); in the higher-order model, they ranged from 0.541 (SOL–OLC) to 0.708 (OLC–SIP). These results confirm that all constructs are empirically distinct from one another, establishing adequate discriminant validity for the measurement model.

Table 3. Discriminant Validity: Heterotrait–Monotrait Ratio of Correlations (HTMT) for the First-Order Constructs.

Construct	DDM	ECP	ENP	EX	MC	SOL	SOP	SP
ECP	0.729							
ENP	0.678	0.709						
EX	0.689	0.561	0.595					
MC	0.565	0.777	0.691	0.760				
SOL	0.629	0.634	0.560	0.607	0.624			
SOP	0.538	0.665	0.722	0.734	0.561	0.790		
SP	0.588	0.764	0.731	0.713	0.769	0.660	0.478	
TR	0.580	0.744	0.700	0.741	0.628	0.770	0.729	0.591

Note. All values < 0.85, confirming discriminant validity [116].

Table 4. Discriminant Validity: Heterotrait–Monotrait Ratio of Correlations (HTMT) for the Higher-Order Model.

Construct	DDM	OLC	SIP
OLC	0.582		
SIP	0.685	0.708	
SOL	0.629	0.541	0.682

Note. All values < 0.85, confirming discriminant validity [116].

4.3. Structural Model Assessment

Before testing the structural hypotheses, collinearity among predictor constructs was examined by calculating variance inflation factors (VIFs) for each endogenous relationship, as recommended by Hair et al. [79]. As presented in Table 5, all predictor VIF values (1.137 to 1.713) fell below 3.3, confirming that collinearity does not threaten the stability of structural path estimates. The construct-level full collinearity VIFs used to assess common method bias ranged from 1.636 (SOL) to 2.881 (ECP) (DDM = 1.645; MC = 2.365; SP = 1.890; EX = 1.799; TR = 2.377; SOL = 1.636; ECP = 2.881; SOP = 2.038; ENP = 2.029), also below 3.3 [100]; the procedure used to obtain these values is described in Section 3.4.

Table 5. Structural Model Assessment: Collinearity, Explanatory Power, Effect Size, and Predictive Relevance.

Outcome	Predictor	Inner VIF	f^2	Effect Size	R^2	Adjusted R^2	Q^2 Predict
OLC	DDM	1.572	0.134	Small	0.689	0.686	0.683
	SOL	1.681	0.673	Large			
	DDM × SOL	1.137	0.028	Large *			
SIP	DDM	1.713	0.080	Small	0.737	0.736	0.706
	OLC	1.713	1.167	Large			

Note. Effect size thresholds: Cohen [84] for main effects; * Kenny [107] for the interaction effect. Q^2 predict obtained from PLSpredict. Model fit: SRMR = 0.064 (estimated model) and 0.065 (saturated model).

The explanatory power of the structural model was assessed using the coefficient of determination (R^2) [72]. OLC demonstrated an R^2 of 0.689 and an adjusted R^2 of 0.686, indicating that DDM, SOL, and the DDM × SOL interaction jointly account for 68.9 percent of the variance in organizational learning capability. SIP demonstrated an R^2 of 0.737 and an adjusted R^2 of 0.736, indicating that DDM and OLC jointly account for 73.7 percent of the variance in sustainable innovation performance. Following the benchmarks of 0.25 (weak), 0.50 (moderate), and 0.75 (substantial) [72], both R^2 values indicate moderate explanatory power, with the R^2 of SIP approaching the substantial level.

Effect sizes (f^2) were computed to assess the relative contribution of each predictor to the endogenous constructs, using Cohen's [84] thresholds of 0.02 (small), 0.15 (medium), and 0.35 (large) for main effects and Kenny's [107] thresholds of 0.005 (small), 0.01 (medium), and 0.025 (large) for interaction effects. As shown in Table 5, SOL demonstrated a large effect on OLC (f^2 = 0.673), OLC demonstrated a large effect on SIP (f^2 = 1.167), and DDM demonstrated small effects on OLC (f^2 = 0.134) and on SIP (f^2 = 0.080). The DDM × SOL interaction had an f^2 of 0.028 on OLC, which corresponds to a large effect by the standards for interaction effects [107,118], consistent with the typically modest absolute magnitude of interaction effects in organizational research [85].

Overall model fit was assessed with the standardized root mean square residual (SRMR). The SRMR was 0.065 for the saturated model and 0.064 for the estimated model, both below the threshold of 0.08 [105,106], indicating acceptable model fit.

Predictive power was assessed using PLSpredict with 10 folds and 10 repetitions [86]. At the construct level, Q^2 predict values of 0.683 for OLC and 0.706 for SIP exceeded zero, indicating predictive relevance (Table 5). At the indicator level (Table 6), all 14 SIP indicators had positive Q^2 predict values (0.276 to 0.436). The PLS-SEM model produced lower RMSE values than the naive linear regression model benchmark for 10 of the 14 indicators, with ECP2, ECP4, ENP1, and SOP5 as exceptions. According to Shmueli et al. [119], this pattern indicates medium predictive power.

Table 6. PLSpredict Results for the Indicators of Sustainable Innovation Performance.

Indicator	Q^2 Predict	PLS-SEM RMSE	PLS-SEM MAE	LM RMSE	LM MAE
ECP1	0.370	0.890	0.684	0.903	0.692
ECP2	0.337	0.632	0.492	0.618	0.492
ECP3	0.434	0.612	0.451	0.639	0.468
ECP4	0.367	0.623	0.466	0.605	0.468
ENP1	0.366	0.688	0.535	0.585	0.454
ENP2	0.436	0.548	0.417	0.554	0.425
ENP3	0.357	0.788	0.610	0.819	0.620
ENP4	0.338	0.833	0.635	0.867	0.657
ENP5	0.276	0.823	0.634	0.835	0.647
SOP1	0.343	0.824	0.621	0.842	0.639
SOP2	0.323	0.814	0.612	0.831	0.637
SOP3	0.373	0.642	0.480	0.657	0.499
SOP4	0.319	0.891	0.690	0.914	0.702
SOP5	0.368	0.643	0.579	0.622	0.488

Note. RMSE = root mean square error; MAE = mean absolute error; LM = linear regression model benchmark. PLSpredict with 10 folds and 10 repetitions.

4.4. Structural Model and Direct Hypothesis Testing

Following confirmation of measurement model validity, the structural model was estimated using SmartPLS 4 with bias-corrected bootstrapping (5000 resamples, 95% confidence intervals) [72]. The SmartPLS path model output, presented in Figure 2, illustrates the estimated path coefficients and significance levels for all direct relationships in the model. Table 7 reports the results for the three direct hypotheses (H1–H3) together with the main effect of SOL on OLC, which is included in the model as part of the moderation test.

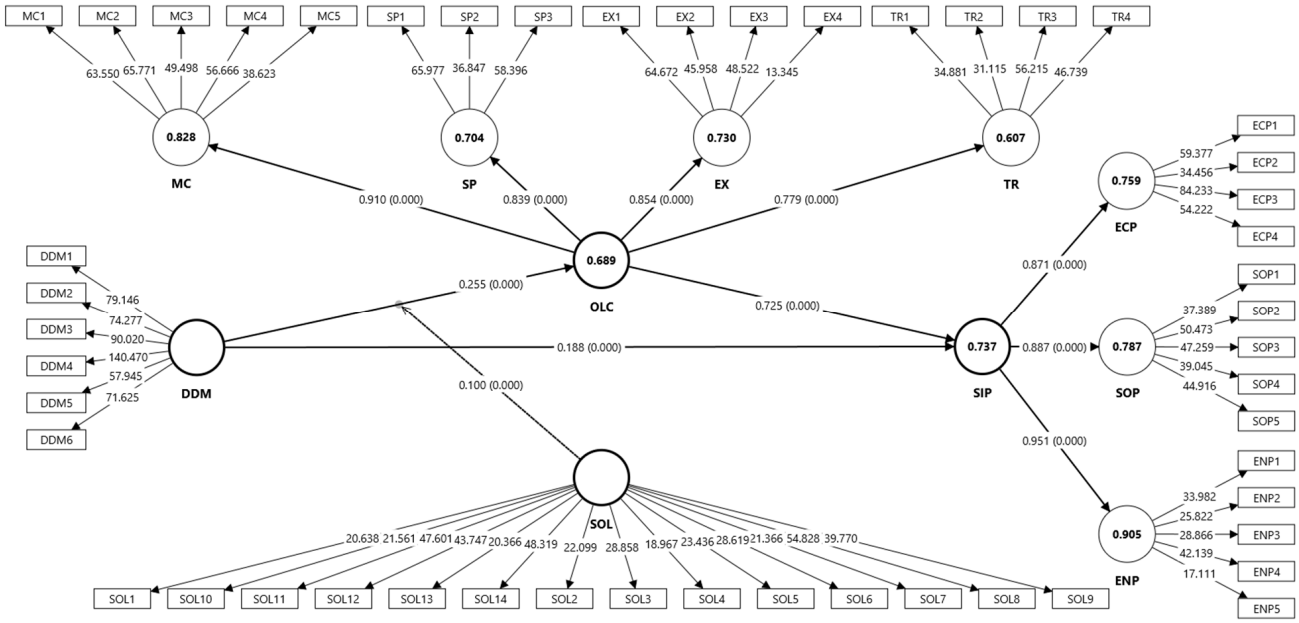


Figure 2. Path Model Results. Note: Solid lines represent direct effects, while dashed lines represent moderating effects.

Table 7. Direct Effects: Results of H1, H2, and H3.

Hyp.	Path	β	SE	t-Value	*p*-Value	95% CI	Decision
H1	DDM → SIP	0.188	0.032	5.859	<0.001	[0.125, 0.252]	Supported
H2	DDM → OLC	0.255	0.033	7.738	<0.001	[0.191, 0.320]	Supported
H3	OLC → SIP	0.725	0.045	16.518	<0.001	[0.656, 0.784]	Supported
–	SOL → OLC	0.592	0.043	13.952	<0.001	[0.527, 0.657]	–

Note. β = standardized path coefficient; SE = standard error; CI = bias-corrected bootstrapped confidence interval (5000 resamples).

H1 predicted that DDM is positively associated with SIP. The results supported this hypothesis (β = 0.188, t = 5.859, $p < 0.001$, 95% CI [0.125, 0.252]), indicating that data-driven decision making is positively and significantly associated with sustainable innovation performance.

H2 predicted that DDM is positively associated with OLC. The results supported this hypothesis (β = 0.255, t = 7.738, $p < 0.001$, 95% CI [0.191, 0.320]), indicating that data-driven decision making is positively and significantly associated with organizational learning capability.

H3 predicted that OLC is positively associated with SIP. The results supported this hypothesis (β = 0.725, t = 16.518, $p < 0.001$, 95% CI [0.656, 0.784]), making the association between organizational learning capability and sustainable innovation performance the strongest path in the model. In addition, SOL was positively associated with OLC (β = 0.592, t = 13.952, $p < 0.001$, 95% CI [0.527, 0.657]).

4.5. Mediation Analysis (H4)

H4 predicted that OLC mediates the relationship between DDM and SIP. Following the bias-corrected bootstrapping approach recommended by Hair et al. [114] and Hayes [111], the direct, indirect, and total effects of DDM on SIP were estimated together [108]. The indirect effect of DDM on SIP through OLC was β = 0.185, t = 7.397, $p < 0.001$, 95% CI [0.136, 0.235]. Because the confidence interval excludes zero, the indirect effect is statistically significant and H4 is supported (Table 8). The direct effect remained significant (β = 0.188, $p < 0.001$, 95% CI [0.125, 0.252]), and the total effect was β = 0.373 (t = 12.686, $p < 0.001$, 95% CI [0.314, 0.431]).

Table 8. Mediation Results: Direct, Indirect, and Total Effects of DDM on SIP (H4).

Effect	Path	β	SE	t-Value	*p*-Value	95% CI	Decision
Direct	DDM → SIP	0.188	0.032	5.859	<0.001	[0.125, 0.252]	
Indirect (H4)	DDM → OLC → SIP	0.185	0.025	7.397	<0.001	[0.136, 0.235]	Supported
Total	DDM → SIP	0.373	0.029	12.686	<0.001	[0.314, 0.431]	

Note. Effects estimated via bias-corrected bootstrapping (5000 resamples). The confidence interval of the indirect effect excludes zero, confirming mediation; the significant direct effect indicates complementary partial mediation [109].

Given that both the direct effect and the indirect effect are statistically significant and have the same sign, the mediation pattern is one of complementary partial mediation [109]. The indirect effect accounts for 49.6 percent of the total effect (variance accounted for = 0.185/0.373), indicating that OLC transmits nearly half of the association between DDM and SIP, while DDM also retains a significant direct association with SIP.

4.6. Moderation Analysis (H5)

H5 predicted that sustainability-oriented leadership positively moderates the relationship between DDM and OLC such that the relationship is stronger when SOL is high. To test this hypothesis, the two-stage approach was applied in SmartPLS 4 to generate the DDM × SOL interaction term from the standardized latent variable scores of DDM and SOL [110]. The interaction term was then included as a predictor of OLC alongside DDM and SOL.

The results confirmed H5: the interaction term DDM × SOL was positively and significantly associated with OLC (β = 0.100, t = 4.521, $p < 0.001$, 95% CI [0.050, 0.137], $f^2 = 0.028$). As presented in Table 9, simple slope analysis showed that the association between DDM and OLC was positive at all three levels of SOL and became stronger as SOL increased: β = 0.155 at low SOL (−1 SD; 95% CI [0.088, 0.232]), β = 0.255 at mean SOL (95% CI [0.191, 0.320]), and β = 0.355 at high SOL (+1 SD; 95% CI [0.265, 0.435]). This indicates that the positive relationship between DDM and OLC is stronger when sustainability-oriented leadership is high.

Table 9. Moderation Results: Interaction Effect of DDM × SOL on OLC and Conditional Effects of DDM (H5).

Path	β	SE	t-Value	*p*-Value	95% CI	Decision
DDM × SOL → OLC (H5)	0.100	0.022	4.521	<0.001	[0.050, 0.137]	Supported
DDM → OLC at low SOL (−1 SD)	0.155	0.036	4.284	<0.001	[0.088, 0.232]	
DDM → OLC at mean SOL	0.255	0.033	7.738	<0.001	[0.191, 0.320]	
DDM → OLC at high SOL (+1 SD)	0.355	0.043	8.276	<0.001	[0.265, 0.435]	

Note. β = standardized path coefficient; SE = standard error. f^2 of the interaction term = 0.028.

Figure 3 presents the simple slope plot for the moderation effect. The slope of the DDM–OLC relationship is steeper at high levels of SOL (+1 SD) than at low levels of SOL (−1 SD), consistent with the positive moderation hypothesis. These results are consistent with SOL acting as a boundary condition under which the association between DDM and organizational learning capability is stronger.

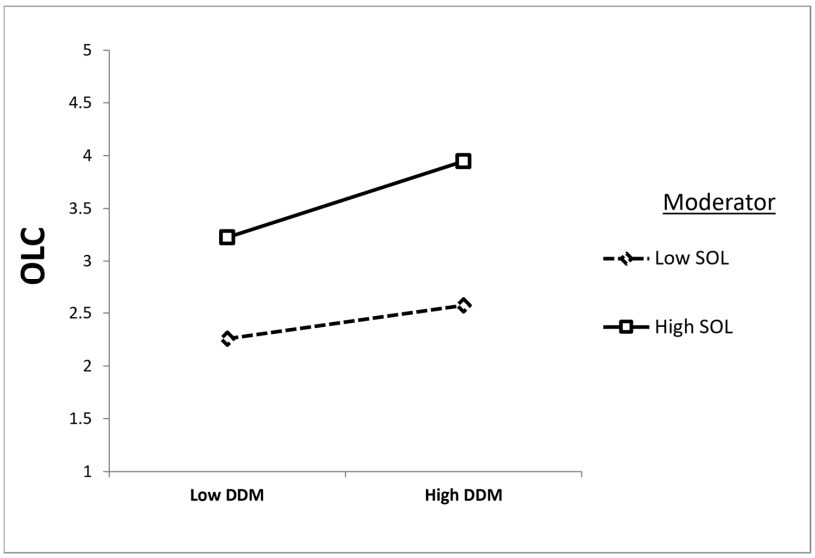


Figure 3. Moderating Effect of Sustainability-Oriented Leadership on the Relationship Between Data-Driven Decision Making and Organizational Learning Capability.

4.7. Moderated Mediation Analysis (H6)

H6 predicted that SOL moderates the indirect relationship between DDM and SIP through OLC such that the indirect effect is stronger when SOL is high. This constitutes a first-stage moderated mediation model [68,69], wherein the moderator (SOL) acts on the first stage of the mediated path (DDM → OLC → SIP). Moderated mediation was tested in SmartPLS 4 using bias-corrected bootstrapping with 5000 resamples [120].

Table 10 presents the conditional indirect effects of DDM on SIP through OLC at three levels of SOL, together with the index of moderated mediation. At low SOL (−1 SD), the conditional indirect effect was β = 0.113 (t = 4.376, $p < 0.001$, 95% CI [0.064, 0.166]). At the mean level of SOL, the conditional indirect effect was β = 0.185 (t = 7.397, $p < 0.001$, 95% CI [0.136, 0.235]). At high SOL (+1 SD), the conditional indirect effect was β = 0.258 (t = 7.530, $p < 0.001$, 95% CI [0.187, 0.323]). All three confidence intervals exclude zero, confirming that the indirect effect of DDM on SIP through OLC is significant at all levels of SOL.

Table 10. Moderated Mediation Results: Conditional Indirect Effects and Index of Moderated Mediation (H6).

Effect	β	SE	t-Value	*p*-Value	95% CI	Decision
Conditional indirect effect at low SOL (−1 SD)	0.113	0.026	4.376	<0.001	[0.064, 0.166]	
Conditional indirect effect at mean SOL	0.185	0.025	7.397	<0.001	[0.136, 0.235]	
Conditional indirect effect at high SOL (+1 SD)	0.258	0.034	7.530	<0.001	[0.187, 0.323]	
Index of moderated mediation (DDM × SOL → OLC → SIP)	0.073	0.017	4.260	<0.001	[0.034, 0.102]	Supported

Note. Conditional indirect effects and the index of moderated mediation estimated via bias-corrected bootstrapping (5000 resamples) [120]. Moderated mediation is supported because the confidence interval of the index excludes zero [70].

The index of moderated mediation was 0.073 (SE = 0.017, t = 4.260, 95% CI [0.034, 0.102], $p < 0.001$). Because the confidence interval excludes zero, moderated mediation is confirmed and H6 is supported [70]. The index indicates that the indirect effect of DDM on SIP through OLC increases by 0.073 for each standard deviation increase in SOL, so the conditional indirect effect at high SOL (0.258) is more than twice that at low SOL (0.113). This pattern indicates that the full DDM–learning–innovation chain is stronger at higher levels of sustainability-oriented leadership: the indirect association between data-driven decision making and sustainable innovation performance through organizational learning capability is stronger where respondents perceive their leaders as actively embodying and communicating sustainability values.

4.8. Robustness Checks

Because respondents were nested within 29 companies and ICC(1) values indicated moderate company-level clustering for DDM (0.084) and SOL (0.091), the robustness of the structural results to the nested structure of the data was examined. With an average cluster size of m = 13.24, the design effects, calculated as $1 + (m - 1) \times ICC(1)$, were 2.03 for DDM and 2.12 for SOL, compared with 1.06 for OLC and 1.51 for SIP [112]. However, the downward bias that clustering introduces into the standard error of a structural path depends jointly on the intraclass correlation of the predictor and that of the outcome, as expressed in the Moulton [113] factor, $1 + (m - 1) \times \rho x \times \rho y$. Because the endogenous constructs of the model, OLC and SIP, exhibited negligible to low clustering, these factors were small (Table 11), implying an inflation of the standard errors of between 0.1 and 2.1 percent.

For the interaction term, the ICC(1) of SOL, the larger of the two component values, was used as a conservative approximation. After applying these corrections, all structural paths remained significant at $p < 0.001$, with corrected t-values ranging from 4.51 (DDM × SOL → OLC) to 16.50 (OLC → SIP). These results indicate that the nested structure of the data does not alter the substantive conclusions and support the analysis of the data at the individual level.

Table 11. Robustness of the Structural Paths to Organizational Clustering.

Path	β	Original t-Value	Moulton Factor	SE Inflation (%)	Corrected t-Value	*p*-Value
DDM → OLC	0.255	7.738	1.005	0.3	7.72	<0.001
SOL → OLC	0.592	13.952	1.006	0.3	13.91	<0.001
DDM × SOL → OLC	0.100	4.521	1.006	0.3	4.51	<0.001
DDM → SIP	0.188	5.859	1.042	2.1	5.74	<0.001
OLC → SIP	0.725	16.518	1.003	0.1	16.50	<0.001

Note. Moulton factor = 1 + (m − 1) × ρx × ρy, with m = 13.24 (average number of respondents per company) and ρ = ICC(1) of the predictor and of the outcome (OLC = 0.005; SIP = 0.041; DDM = 0.084; SOL = 0.091). SE inflation = ($\sqrt{}$Moulton factor − 1) × 100. Corrected t-value = original t-value/$\sqrt{}$Moulton factor. For the interaction term, the ICC(1) of SOL was used as a conservative approximation.

5. Discussion

This study tested a theoretically grounded moderated mediation model linking data-driven decision making, organizational learning capability, sustainability-oriented leadership, and sustainable innovation performance in Libya's oil and gas sector. The results support all six hypotheses and are consistent with the proposed mechanisms and boundary conditions through which DDM is associated with sustainable innovation performance. Because the design is cross-sectional and the constructs were measured through employees' perceptions of their organizations, these relationships are interpreted as perceived associations rather than as causal effects. Throughout this section, we therefore distinguish between what the data establish, namely the direction, strength, and conditional pattern of the associations among the constructs, and the theoretical mechanisms proposed to explain them, which are consistent with these associations but were not observed directly.

The confirmation of H1 (DDM → SIP: β = 0.188, $p < 0.001$) indicates that data-driven decision making is positively associated with sustainable innovation performance. This finding is consistent with the dynamic capabilities perspective [4,5], which positions DDM as a sensing and seizing capability through which organizations identify sustainability innovation opportunities, monitor environmental and social performance indicators, and direct innovation investment toward sustainability goals. In the context of Libya's oil and gas sector, real-time operational data, emissions indicators, safety records, and environmental monitoring systems can provide the informational infrastructure through which data-driven firms may identify process improvement opportunities, reduce environmental risks, and achieve economically viable sustainable operations. This result aligns with Wang et al. [10], who report a positive association between big data capability and sustainability-oriented innovation performance among Chinese firms; with Cheng et al. [9], who show that configurations of digital technology adoption are associated with high sustainable innovation performance in Chinese high-tech manufacturing; and with Goraya et al. [7], who find that DDM is positively associated with organizational performance in a hostile environment. The direct association is, however, modest in size ($f^2 = 0.080$), which indicates that data-driven decision making on its own accounts for only a limited share of sustainable

innovation performance; as discussed below, a comparable share of its total association with SIP is transmitted through organizational learning capability.

The support for H2 (DDM → OLC: β = 0.255, $p < 0.001$) indicates that data-driven decision making is positively associated with organizational learning capability. This finding reflects the theoretical argument, grounded in organizational learning theory [25,41,42], that DDM practices institutionalize evidence-based inquiry, build organizational knowledge repositories, and promote the cross-functional knowledge sharing and experimentation that characterize learning organizations. In the oil and gas context, the systematic use of operational dashboards, maintenance databases, and environmental performance data may accumulate organizational memory artifacts that strengthen knowledge transfer and integration, while the habit of data-based decision making may promote openness to new evidence and experimentation with process improvements. These processes were not measured directly, however, and the present data show only that organizations whose employees report stronger data-driven practices also report stronger learning capability. This finding is consistent with Wang et al. [10], who find that big data capability is strongly associated with intellectual capital, the knowledge stocks on which organizational learning builds, and with Goraya et al. [7], who conceptualize DDM as combining decision automation with collective sense-making among managers. At the same time, the effect size of DDM on OLC was small ($f^2 = 0.134$) compared with that of SOL ($f^2 = 0.673$), which suggests that, in this context, the learning capability of an organization is more closely tied to its leadership orientation than to its data practices alone.

The confirmation of H3 (OLC → SIP: β = 0.725, $p < 0.001$) indicates that organizational learning capability is strongly and positively associated with sustainable innovation performance. This is the largest path coefficient in the model ($f^2 = 1.167$), underscoring the centrality of organizational learning processes for sustainable innovation. The coefficient is almost four times that of the direct DDM → SIP path (0.188), a contrast that is theoretically meaningful: in this sample, the capacity of organizations to acquire, share, and apply knowledge is far more strongly associated with sustainable innovation performance than the use of data in decision making as such. A similar pattern appears in Wang et al. [10], where intellectual capital was more strongly associated with sustainability-oriented innovation performance (β = 0.579) than big data capability was directly (β = 0.241), and in Iqbal and Ahmad [20], who report a strong association between organizational learning and sustainable performance (β = 0.625). This result also aligns with Alegre and Chiva [18], Migdadi [19], and Gomes et al. [64], who report positive associations between OLC and innovation outcomes in industrial, service, and knowledge-intensive contexts. The four dimensions of OLC, namely managerial commitment, systems perspective, openness and experimentation, and knowledge transfer and integration, are each theorized to contribute mechanisms through which learning routines are converted into sustainable innovation outcomes: managerial commitment directs resources toward sustainability innovation; the systems perspective ensures that sustainability knowledge is shared across organizational units; openness and experimentation enables prototyping of sustainable solutions; and knowledge transfer and integration ensures that sustainability insights are embedded in organizational memory and practice. The present design does not test these dimension-specific mechanisms separately; the strong loadings of all four dimensions on the higher-order OLC construct (0.779 to 0.910) indicate only that they reflect a common learning capability.

The confirmation of H4, establishing OLC as a partial mediator of the DDM-SIP relationship (indirect effect: β = 0.185, $p < 0.001$, 95% CI [0.136, 0.235]), is the central finding of this study regarding mechanism. Statistically, it indicates that a substantial part of the association between DDM and SIP is shared with OLC; theoretically, this pattern is consistent

with the proposition that organizational learning capability is the means through which DDM is linked to sustainable innovation performance. The indirect effect is almost equal in size to the direct effect (0.188) and accounts for 49.6 percent of the total effect (0.373), indicating complementary partial mediation [109]. This finding is consistent with the two-stage mediation logic proposed in the theoretical framework: DDM is associated with organizational learning capability through institutionalizing evidence-based inquiry and building shared knowledge repositories, and OLC then channels this analytical and knowledge capacity into sustainable innovation performance by enabling firms to systematically apply learning to the development of economically, socially, and environmentally sustainable innovations. This pattern parallels prior evidence that knowledge-based mechanisms transmit the association between data capabilities and sustainability-oriented innovation [10], and that organizational learning capability acts as an intermediate mechanism between strategic orientations and innovation outcomes [18,44,65]. It should be emphasized, however, that with cross-sectional data, a significant indirect effect shows that the pattern of associations is consistent with mediation; it does not establish the temporal ordering of DDM, OLC, and SIP, and alternative orderings, for example that organizations with strong learning capability are more inclined to adopt data-driven practices, cannot be ruled out. The presence of partial rather than full mediation indicates that DDM retains a significant direct association with SIP, consistent with the dynamic capabilities view that some of the value of DDM may be realized through immediate reconfiguration without requiring the full organizational learning cycle. Together, these results suggest an answer to the central "how" question of the study: data-driven decision making is associated with sustainable innovation performance both directly and indirectly through organizational learning capability, a pattern consistent with the proposed role of the organizational learning system in converting data into sustainable innovation capability.

The support for H5 (DDM $\times$ SOL $\rightarrow$ OLC: $\beta = 0.100$, $p < 0.001$) indicates that sustainability-oriented leadership positively moderates the DDM-OLC relationship such that the positive association between DDM and OLC is stronger when SOL is high. The simple slopes show that the association between DDM and OLC rises from 0.155 at low SOL to 0.355 at high SOL, more than doubling across the range of leadership orientation while remaining positive even when SOL is low. Sustainability-oriented leadership therefore conditions how strongly data-driven practices are reflected in learning capability rather than determining whether they are reflected at all. This finding advances the sustainability leadership literature by identifying SOL as a boundary condition under which the association between data-driven decision making and organizational learning is stronger. A plausible explanation, which was not tested directly, is that when leaders consistently model sustainability-oriented values, communicate sustainability as a strategic priority, and reward sustainability-directed learning behaviors, the organizational climate becomes more receptive to channeling data-driven insights into sustainability-relevant knowledge development. This result is consistent with evidence that sustainable leadership is positively associated with organizational learning [20], with knowledge management processes [22], and with knowledge management and dynamic capabilities [35,121], as well as with the finding that sustainability-oriented leadership shapes the normative context in which employees interpret organizational initiatives [45]. It also extends this work: whereas these studies treat sustainable leadership as an antecedent of learning, the present results indicate that it also conditions the extent to which another capability, DDM, is associated with learning. The large direct association between SOL and OLC ($\beta = 0.592$, $f^2 = 0.673$) further underlines that leadership orientation is closely tied to the learning capability of oil and gas organizations. Avery and Bergsteiner [26] similarly theorize that sustainability

leadership fosters a systemic organizational orientation that amplifies the translation of analytical capabilities into long-term sustainable performance.

The confirmation of H6, that SOL moderates the full indirect DDM-OLC-SIP path through a significant index of moderated mediation (index = 0.073, 95% CI [0.034, 0.102], $p < 0.001$), constitutes the most theoretically significant finding of this study. The conditional indirect effects increase from $\beta = 0.113$ at low SOL to $\beta = 0.258$ at high SOL, indicating that the indirect association between DDM and SIP through OLC is more than twice as strong when SOL is high compared to when it is low. Because SOL operates on the first stage of the indirect path, this result does not mean that SOL mediates the DDM-SIP relationship; rather, SOL moderates the strength of the mediated path through its moderation of the DDM-OLC link. This finding integrates dynamic capabilities theory, organizational learning theory, and the sustainability leadership perspective into a unified explanation of how, and under what leadership conditions, DDM is associated with sustainable innovation performance. The proposed interpretation is that when sustainability-oriented leaders direct the organizational learning system toward sustainability goals, data-driven decision making becomes more strongly associated with sustainable innovation through learning; the data show that the indirect association is stronger where SOL is perceived as high, but not how leaders bring this about. This positions SOL not merely as a direct correlate of sustainability outcomes but as a condition under which the DDM–learning–innovation chain is stronger, consistent with Metcalf and Benn [23]. It also accords with the view that digital capabilities are neutral with respect to sustainability and that their sustainability returns depend on the strategic orientation under which they are deployed [34,50].

6. Implications, Limitations, and Future Research

6.1. Theoretical Implications

This study advances the strategic leadership and sustainable innovation literature by providing evidence consistent with the proposition that sustainability-oriented leadership conditions the extent to which data-driven decision making is associated with sustainable innovation performance through organizational learning capability, particularly in complex and institutionally uncertain emerging economy environments. This contribution should be positioned carefully against existing work, because the individual relationships in the model are not new. The performance value of AI-enabled and data-related capabilities has been shown to be transmitted through data-driven culture and organizational learning [21]; big data capability has been linked to sustainability-oriented innovation through intellectual capital [10]; business analytics capability and agility have been identified as antecedents of DDM [7]; digital transformation has been associated with sustainable innovation performance, with technology–business alignment and environmental uncertainty shaping this association [29]; and sustainability-oriented leadership has been linked to learning and knowledge management processes [20,22]. Relative to these studies, the present contribution is specific and incremental: it combines the learning-mediated logic of data capabilities with a leadership boundary condition placed on the data-to-learning stage, applies this configuration to sustainable innovation performance rather than to financial or general performance, and tests it in a conflict-affected resource sector. The proposition that emerges from this integration is that the sustainability value of DDM is learning-contingent, because its association with SIP is transmitted to a large extent through organizational learning capability, and leadership-contingent, because sustainability-oriented leadership conditions the stage at which data are converted into learning. Because the evidence is cross-sectional and perceptual, this proposition is supported by the pattern of associations observed here, but longitudinal or quasi-experimental evidence would be required to establish it as a causal process.

First, it extends Dynamic Capabilities Theory by providing evidence consistent with DDM functioning as a sensing and seizing capability that is associated with sustainable innovation performance both directly and through the organizational learning system. Previous applications of DCT in the sustainability domain have examined data and analytics capabilities [7,10] but have rarely traced the pathway from data-driven decision making to sustainable innovation outcomes through learning processes. The results qualify the DCT view in an important way. The direct association between DDM and SIP was small, whereas nearly half of its total association was transmitted through learning, which is consistent with the argument that sensing adds value only when it is followed by reconfiguration and that reconfiguration rests on deliberate learning [5,33]. DDM therefore appears to behave as a dynamic capability whose sustainability value is realized largely through the learning routines it feeds, consistent with the treatment of sustainability-related scanning and learning activities as microfoundations of dynamic capabilities for sustainability [34]. This study thus helps to connect data-sensing capabilities with sustainable innovation outcomes.

Second, the study advances Organizational Learning Theory by providing evidence consistent with OLC as a mechanism through which DDM is linked to sustainable innovation performance in a resource-sector context. The finding that OLC partially mediates the DDM-SIP relationship is consistent with the theoretical proposition that organizational learning processes are important intermediaries between analytical decision-making capabilities and sustainable innovation outcomes [17,24], and extends this theoretical logic to the specific context of an emerging economy's resource extraction sector. The strength of the OLC-SIP association, the largest in the model, also suggests that learning capability is not only a conduit for data but a central correlate of sustainable innovation in its own right.

Third, the study contributes to the sustainability leadership literature by identifying SOL as a first-stage moderator of the DDM-OLC-SIP indirect path, showing that the full DDM–learning–innovation chain is stronger at higher levels of SOL and consistent with leadership orientation functioning as a boundary condition. This positions sustainability-oriented leadership at a specific point in the process: it conditions the conversion of data-driven insights into learning, rather than acting only as a direct antecedent of sustainability outcomes. This interpretation is consistent with Nguyen [22], who found that sustainability-oriented leadership was associated with knowledge management processes but not directly with green innovation, and it extends the leadership–learning link reported by Iqbal and Ahmad [20] by showing that leadership orientation also shapes how another capability is associated with learning. This finding responds to calls for research that identifies the organizational conditions under which sustainability capabilities are most effectively translated into sustainable innovation outcomes [23,47].

Fourth, the study makes an empirical contribution to emerging economy and MENA region research by providing evidence from Libya's oil and gas sector, a strategically important but empirically underexplored context [122,123]. The findings indicate that the theoretical relationships posited by DCT, OLT, and the sustainability leadership perspective are supported in institutionally complex and resource-sector-specific organizational environments, extending the contextual scope of these theoretical frameworks.

6.2. Practical Implications

The findings of this study carry several practical implications for managers, leaders, and policymakers in Libya's oil and gas sector and comparable resource-intensive industries. Because the findings are based on cross-sectional associations, these implications indicate where managerial attention is likely to be most productive rather than guaranteeing returns from specific investments.

First, managers should invest in organizational data infrastructure, including operational dashboards, real-time environmental monitoring systems, maintenance data platforms, and sustainability reporting tools, as these data systems not only support decision quality but are also associated with stronger organizational learning capabilities and, through them, with sustainable innovation performance. The finding that DDM is associated with SIP both directly and through OLC suggests that DDM investments may yield returns through multiple pathways, which supports a business case for data system development in the sector. These findings carry direct implications for strategic leaders in emerging economies who seek to steer organizational transformation toward sustainability under conditions of institutional complexity and resource constraints: they suggest that sustainability-oriented leadership is not merely a values statement but a condition under which data-driven practices are more strongly associated with learning and sustainable innovation.

Second, sustainability and health, safety, and environment departments should systematically leverage environmental, safety, and production data to support sustainable innovation projects, using data-driven performance monitoring to identify opportunities for emissions reduction, waste minimization, energy efficiency improvement, and community welfare enhancement. Analytical approaches that combine causal inference with predictive modeling can help such departments anticipate operational risks before they materialize [40]. The OLC-SIP path coefficient ($\beta = 0.725$) indicates that the conversion of data insights into organizational learning is the strongest correlate of sustainable innovation in this model, suggesting that the quality of the learning process matters more than the volume of data collected.

Third, organizational leaders should prioritize sustainability-oriented leadership behaviors, including explicit communication of sustainability priorities, formal recognition of sustainability innovation achievements, modelling of ethical and environmental decision making, and willingness to correct sustainability-related errors, as the moderation results indicate that the association between DDM and organizational learning, and through it with sustainable innovation, is stronger where SOL is perceived as high. Where sustainability-oriented leadership was perceived as high, the association between DDM and OLC was more than twice as strong as where it was perceived as low.

Fourth, HR and training units should invest in building employee capabilities in data interpretation, sustainability problem-solving, and organizational learning routines, ensuring that data literacy is distributed across departments and functional areas rather than concentrated in IT units. The systems perspective dimension of OLC indicates that inter-unit coordination and shared understanding of organizational sustainability objectives are critical enablers of the DDM-OLC-SIP pathway.

Fifth, policymakers and regulators in Libya should promote digital sustainability reporting requirements, sector-wide environmental performance monitoring systems, and shared data platforms for the oil and gas sector, recognizing that the development of national data infrastructure supports not only regulatory compliance but also the organizational learning capabilities that are associated with sustainable innovation across the sector.

6.3. Limitations and Future Research Directions

This study has several limitations that should be acknowledged and that point to productive directions for future research. The cross-sectional design captures relationships at a single point in time, precluding causal inference and limiting the study's ability to track changes in DDM, OLC, and SIP over time. Future research should employ longitudinal designs to examine whether DDM investments are followed by OLC and SIP improvements over time, and whether the moderating effect of SOL strengthens or weakens as

organizations develop sustainability maturity. The use of self-reported, perceptual data from individual respondents introduces the possibility of response biases and limits the objectivity of performance indicators. Because all constructs, including both the predictors and the outcomes, were measured in the same questionnaire completed by the same respondents at a single point in time, common method variance may have inflated the observed associations, in particular the strong association between OLC and SIP. The procedural remedies, Harman's single-factor test, and the full collinearity assessment reported in Section 3.4 reduce this concern but cannot rule it out, because such diagnostics detect only strong and pervasive method effects. Future research should therefore separate the sources or the timing of measurement, for example by obtaining SIP ratings from senior managers and DDM and OLC ratings from employees, or by collecting predictor and outcome data in separate waves, and should supplement survey data with objective environmental and financial performance records [81].

In addition, although DDM, OLC, SOL, and SIP are organizational-level constructs, they were measured through individual employees' perceptions, and the results should therefore be interpreted as perceived organizational characteristics rather than as objective organizational attributes. Respondents were also nested within 29 companies, and ICC(1) values of up to 0.091 (for SOL) indicate that part of the variance in responses is attributable to company membership. Although the robustness checks reported in Section 4.8 indicate that this nesting does not alter the substantive conclusions, future studies covering a larger number of organizations could aggregate responses to the company level or apply multilevel modeling to separate individual and organizational sources of variance.

The sample was obtained through non-probability purposive sampling, with human resources departments inviting employees who were willing to participate, and only 29 of the 48 companies in the sampling frame are represented in the final sample. Employees who volunteer may hold more favorable views of their organizations than non-participants, and the findings cannot be generalized statistically to the Libyan oil and gas sector as a whole. Replication using probability-based sampling of both companies and employees would strengthen external validity. Furthermore, PLSpredict indicated medium rather than high predictive power, with the linear benchmark outperforming the PLS-SEM model for four of the fourteen SIP indicators, which suggests that the measurement of economic and social innovation outcomes in the oil and gas context could be refined in future work. In addition, SIP was specified as a reflective–reflective higher-order construct on the grounds that its economic, social, and environmental dimensions are manifestations of an integrated sustainable innovation capacity (Section 3.3). Where research is concerned with the distinct contribution of each dimension, or where the dimensions are expected to involve trade-offs, a reflective–formative specification may be more appropriate, and future studies could compare the two specifications empirically.

The single-sector focus on Libya's oil and gas industry, while theoretically generative, further limits the generalizability of findings; comparative studies across sectors such as manufacturing, telecommunications, and banking in Libya, or cross-national comparisons across MENA economies, would establish the boundary conditions of the model. Finally, the quantitative design does not capture the process dynamics through which DDM becomes organizational learning in practice; qualitative case study research exploring how specific data-driven practices are absorbed into learning routines and directed toward sustainable innovation would provide rich complementary insights [124].

7. Conclusions

This study examined how and when data-driven decision making is associated with sustainable innovation performance in Libya's oil and gas sector. Using survey data from

384 employees of 29 companies analyzed with PLS-SEM, it found support for all six hypotheses. DDM was positively associated with SIP (β = 0.188) and with OLC (β = 0.255), and OLC was strongly associated with SIP (β = 0.725). OLC partially mediated the relationship between DDM and SIP, transmitting 49.6 percent of the total effect (indirect effect = 0.185). The association between DDM and OLC was stronger at higher levels of SOL (interaction β = 0.100), and the indirect association between DDM and SIP through OLC rose from 0.113 at low SOL to 0.258 at high SOL (index of moderated mediation = 0.073).

The study therefore answers its central question as follows: data-driven decision making is associated with sustainable innovation performance largely through organizational learning capability, and this learning pathway is stronger where leaders are oriented toward sustainability. Although these conclusions rest on cross-sectional, perception-based evidence, they suggest that organizations in resource-intensive and institutionally uncertain settings are most likely to realize the sustainability potential of data-driven decision making when investments in data are matched by investments in organizational learning and in sustainability-oriented leadership.

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Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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Appendix A

Table A1. Measurement Items and Sources.

Code	Item	Source
Data-driven decision making (DDM)	To what extent does your organization:	Adapted from Goraya et al. [7]
DDM1	Use data-based insights to create new services, products, or operational solutions.	
DDM2	Depend on data-based insights when making important decisions.	
DDM3	Remain open to new ideas that challenge current practices based on data-driven insights.	
DDM4	Have sufficient data available to support decision making.	
DDM5	Use data-based insights to respond quickly to changes in the business environment.	
DDM6	Use real-time data to make timely decisions.	
Organizational learning capability (OLC)	Managerial commitment (MC)	Adapted from Jerez-Gomez et al. [17]
MC1	Managers frequently involve employees in important decision-making processes.	

Table A1. *Cont.*

Code	Item	Source
MC2	Employee learning is considered an important investment in this organization.	
MC3	Management supports changes that help the organization adapt to new environmental conditions.	
MC4	Employee learning capability is considered a key factor in this organization.	
MC5	Innovative ideas that work are recognized and rewarded in this organization.	
	Systems perspective (SP)	
SP1	Employees have general knowledge of this organization's objectives.	
SP2	Departments, work teams, and individuals understand how they contribute to achieving overall organizational objectives.	
SP3	Departments, work teams, and individuals are interconnected and work together in a coordinated way.	
	Openness and experimentation (EX)	
EX1	This organization promotes experimentation and innovation as ways to improve work processes.	
EX2	This organization follows what other organizations in the sector are doing and adopts useful practices and techniques.	
EX3	Experiences and ideas from external sources, such as advisors, customers, training providers, and partners, are considered useful for organizational learning.	
EX4	Employees can express their opinions and make suggestions about existing procedures and work methods.	
	Knowledge transfer and integration (TR)	
TR1	Errors and failures are discussed and analyzed at all levels of this organization.	
TR2	Employees have opportunities to discuss new ideas, programs, and activities that may be useful to the organization.	
TR3	Teamwork is a usual and encouraged way of working in this organization.	
TR4	This organization has tools, such as manuals, databases, files, and routines, that preserve knowledge gained from previous experiences.	
Sustainability-oriented leadership (SOL)		Adapted from Iqbal et al. [45] and Iqbal and Ahmad [20]
SOL1	Organizational leadership acts in a socially responsible manner.	
SOL2	Organizational leadership acts in an environmentally responsible manner.	
SOL3	Organizational leadership acts in an ethically responsible manner.	
SOL4	Organizational leadership makes decisions while considering the interests of the entire organization.	
SOL5	Organizational leadership officially recognizes mistakes that affect sustainability.	
SOL6	Organizational leadership is willing to correct mistakes that affect sustainability.	
SOL7	Organizational leadership uses innovative methods to resolve sustainability-related issues.	
SOL8	Organizational leadership attempts to create value through sustainable efforts.	

Table A1. *Cont.*

Code	Item	Source
SOL9	Organizational leadership puts organizational purpose before short-term profit.	
SOL10	Organizational leadership balances social responsibility with financial performance.	
SOL11	Organizational leadership demonstrates commitment to sustainability during periods of change.	
SOL12	Organizational leadership is concerned about how sustainability decisions affect employees.	
SOL13	Organizational leadership communicates sustainability-related decisions to those involved.	
SOL14	Organizational leadership attempts to build a culture of sustainability through communication.	
Sustainable innovation performance (SIP)	Economic innovation performance (ECP)	Adapted from Cheng et al. [9]
ECP1	Our organization's sustainable innovation activities have decreased the cost of materials purchased.	
ECP2	Our organization's sustainable innovation activities have decreased the cost of energy consumption.	
ECP3	Our organization's sustainable innovation activities have improved return on investment.	
ECP4	Our organization's sustainable innovation activities have improved earnings per share.	
	Social innovation performance (SOP)	
SOP1	Our organization's sustainable innovation activities have improved stakeholder welfare.	
SOP2	Our organization's sustainable innovation activities have improved community health and safety.	
SOP3	Our organization's sustainable innovation activities have reduced environmental risks to the general public.	
SOP4	Our organization's sustainable innovation activities have improved employees' occupational health and safety.	
SOP5	Our organization's sustainable innovation activities have improved awareness and protection of community rights.	
	Environmental innovation performance (ENP)	
ENP1	Our organization's sustainable innovation activities have reduced emissions.	
ENP2	Our organization's sustainable innovation activities have reduced waste.	
ENP3	Our organization's sustainable innovation activities have decreased the consumption of hazardous, harmful, or toxic materials.	
ENP4	Our organization's sustainable innovation activities have decreased the frequency of environmental accidents.	
ENP5	Our organization's sustainable innovation activities have increased energy savings through conservation and efficiency improvements.	

References

1. Davenport, T.H.; Harris, J.G. *Competing on Analytics: The New Science of Winning*; Harvard Business Review Press: Boston, MA, USA, 2007.
2. Provost, F.; Fawcett, T. *Data Science for Business: What You Need to Know about Data Mining and Data-Analytic Thinking*; O'Reilly Media: Sebastopol, CA, USA, 2013.

3. Ayoub, H.S.; Aljuhmani, H.Y. Artificial Intelligence Capabilities as a Catalyst for Enhanced Organizational Performance: The Importance of Cultivating a Data-Driven Culture. In *Achieving Sustainable Business Through AI, Technology Education and Computer Science: Volume 2: Teaching Technology and Business Sustainability*; Hamdan, A., Ed.; Springer Nature: Cham, Switzerland, 2024; pp. 345–356.
4. Teece, D.J.; Pisano, G.; Shuen, A. Dynamic Capabilities and Strategic Management. *Strateg. Manag. J.* **1997**, *18*, 509–533. [CrossRef]
5. Teece, D.J. Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. *Strateg. Manag. J.* **2007**, *28*, 1319–1350. [CrossRef]
6. Shamim, S.; Zeng, J.; Shariq, S.M.; Khan, Z. Role of Big Data Management in Enhancing Big Data Decision-Making Capability and Quality among Chinese Firms: A Dynamic Capabilities View. *Inf. Manag.* **2019**, *56*, 103135. [CrossRef]
7. Goraya, M.A.S.; Kemal, A.A.; Xu, M.; Shareef, M.A.; Akram, M.S. Leveraging Digital Transformation Strategy and Data-Driven Decision-Making to Improve Organisational Performance in a Hostile Environment. *Ind. Manag. Data Syst.* **2025**, *126*, 650–677. [CrossRef]
8. Chen, Y.-S. The Driver of Green Innovation and Green Image—Green Core Competence. *J. Bus. Ethics* **2008**, *81*, 531–543. [CrossRef]
9. Cheng, C.; Zhang, M.; Dai, J.; Yang, Z. When Does Digital Technology Adoption Enhance Firms' Sustainable Innovation Performance? A Configurational Analysis in China. *IEEE Trans. Eng. Manag.* **2024**, *71*, 1555–1568. [CrossRef]
10. Wang, N.; Xie, W.; Huang, Y.; Ma, Z. Big Data Capability and Sustainability Oriented Innovation: The Mediating Role of Intellectual Capital. *Bus. Strategy Environ.* **2023**, *32*, 5702–5720. [CrossRef]
11. Ramadan, A.A.; Alzughid, S.; Al-Bishari, A.S.A.; Elabani, F.A.H. Artificial Intelligence as a Catalyst for Sustainable Development in Libya: An Integrated Analysis of Pathways, Challenges, and Strategic Frameworks. In *Proceedings of the 2026 IEEE International Conference on Smart Sustainable Systems for Computer and Engineering Applications (3SCEA), Cairo, Egypt, 19–21 April 2026*; IEEE: New York, NY, USA, 2026; pp. 1088–1092.
12. Vandewalle, D. *A History of Modern Libya*; Cambridge University Press: New York, NY, USA, 2012.
13. Lacher, W. *Libya's Fragmentation: Structure and Process in Violent Conflict*; I.B. Tauris: London, UK, 2020.
14. Altabouli, A.A.; Çelebi, A.İ. Digital Leadership and the Innovation Process in Libyan Organizations: The Mediating Roles of Technological Readiness and Organizational Sustainability. *Sustainability* **2026**, *18*, 9176. [CrossRef]
15. Abduljalil, M.; Alawi, N.; Masaud, K. Beyond Satisfaction: The Resilience Pathway Self-Efficacy as the Critical Mediator Between Job Satisfaction and Performance in Libya's Conflict-Affected Oil Sector. *J. Reprod. Res.* **2025**, *2*, 87–108.
16. Brynjolfsson, E.; McElheran, K. The Rapid Adoption of Data-Driven Decision-Making. *Am. Econ. Rev.* **2016**, *106*, 133–139. [CrossRef]
17. Jerez-Gómez, P.; Céspedes-Lorente, J.; Valle-Cabrera, R. Organizational Learning Capability: A Proposal of Measurement. *J. Bus. Res.* **2005**, *58*, 715–725. [CrossRef]
18. Alegre, J.; Chiva, R. Linking Entrepreneurial Orientation and Firm Performance: The Role of Organizational Learning Capability and Innovation Performance. *J. Small Bus. Manag.* **2013**, *51*, 491–507. [CrossRef]
19. Migdadi, M.M. Organizational Learning Capability, Innovation and Organizational Performance. *Eur. J. Innov. Manag.* **2019**, *24*, 151–172. [CrossRef]
20. Iqbal, Q.; Ahmad, N.H. Sustainable Development: The Colors of Sustainable Leadership in Learning Organization. *Sustain. Dev.* **2021**, *29*, 108–119. [CrossRef]
21. Ayoub, H.S.; Sopuru, J.C. Reconfiguring Strategic Capabilities in the Digital Era: How AI-Enabled Dynamic Capability, Data-Driven Culture, and Organizational Learning Shape Firm Performance. *Sustainability* **2026**, *18*, 1157. [CrossRef]
22. Nguyen, T.P.L. Sustainability-Oriented Leadership, Knowledge Management Processes and Green Innovation in Service Companies. *J. Knowl. Manag.* **2025**, *29*, 2986–3010. [CrossRef]
23. Metcalf, L.; Benn, S. Leadership for Sustainability: An Evolution of Leadership Ability. *J. Bus. Ethics* **2013**, *112*, 369–384. [CrossRef]
24. Argote, L.; Miron-Spektor, E. Organizational Learning: From Experience to Knowledge. *Organ. Sci.* **2011**, *22*, 1123–1137. [CrossRef]
25. Senge, P.M. *The Fifth Discipline: The Art & Practice of the Learning Organization*; Doubleday: New York, NY, USA, 2006.
26. Avery, G.C.; Bergsteiner, H. Sustainable Leadership Practices for Enhancing Business Resilience and Performance. *Strategy Leadersh.* **2011**, *39*, 5–15. [CrossRef]
27. Hambrick, D.C.; Mason, P.A. Upper Echelons: The Organization as a Reflection of Its Top Managers. *Acad. Manag. Rev.* **1984**, *9*, 193–206. [CrossRef]
28. Bass, B.M.; Avolio, B.J. Transformational Leadership And Organizational Culture. *Int. J. Public Adm.* **1994**, *17*, 541–554. [CrossRef]
29. Lin, J.; Mao, M. How Does Digital Transformation Affect Sustainable Innovation Performance? The Pivotal Roles of Digital Technology-Business Alignment and Environmental Uncertainty. *Sustain. Dev.* **2024**, *32*, 3163–3181. [CrossRef]
30. Fanes, S.E. The Impact of International Marketing on International Competitiveness: A Case Study of the Mellitah Oil & Gas Complex Libyan Branch. *J. Intell. Decis. Mak. Inf. Sci.* **2026**, *3*, 781–802. [CrossRef]

31. Durman, S.; Iyiola, K.; Alzubi, A.B.; Aljuhmani, H.Y. Dynamic Capabilities in Action: Digital Capability, Business Model Innovation and Absorptive Capacity. *Manag. Decis.* **2025**, 1–36. [CrossRef]
32. Wei, C. Artificial Intelligence, Sustainable Innovation, and Organizational Transformation: An Integrated Strategic Framework for Contemporary Business Ecosystems. *Strateg. Bus. Res.* **2026**, *2*, 100240. [CrossRef]
33. Zollo, M.; Winter, S.G. Deliberate Learning and the Evolution of Dynamic Capabilities. *Organ. Sci.* **2002**, *13*, 339–351. [CrossRef]
34. Buzzao, G.; Rizzi, F. On the Conceptualization and Measurement of Dynamic Capabilities for Sustainability: Building Theory through a Systematic Literature Review. *Bus. Strategy Environ.* **2021**, *30*, 135–175. [CrossRef]
35. Achmad, F.; Inrawan Wiratmadja, I. Driving Sustainable Performance in SMEs Through Frugal Innovation: The Nexus of Sustainable Leadership, Knowledge Management, and Dynamic Capabilities. *IEEE Access* **2024**, *12*, 103329–103347. [CrossRef]
36. Eisenhardt, K.M.; Martin, J.A. Dynamic Capabilities: What Are They? *Strateg. Manag. J.* **2000**, *21*, 1105–1121. [CrossRef]
37. Winter, S.G. Understanding Dynamic Capabilities. *Strateg. Manag. J.* **2003**, *24*, 991–995. [CrossRef]
38. Alsafadi, Y.; Aljuhmani, H.Y. The Influence of Entrepreneurial Innovations in Building Competitive Advantage: The Mediating Role of Entrepreneurial Thinking. *Kybernetes* **2023**, *53*, 4051–4073. [CrossRef]
39. Akter, S.; Wamba, S.F.; Gunasekaran, A.; Dubey, R.; Childe, S.J. How to Improve Firm Performance Using Big Data Analytics Capability and Business Strategy Alignment? *Int. J. Prod. Econ.* **2016**, *182*, 113–131. [CrossRef]
40. Hafaf, E.; Alzubi, A.B.; Iyiola, K.; Aljuhmani, H.Y. A Simulation-Based Hybrid Causal Predictive Framework for Stockout Risk Analysis in Supply Chain. *PLoS ONE* **2026**, *21*, e0350429. [CrossRef] [PubMed]
41. Argyris, C.; Schon, D.A. *Organizational Learning: A Theory of Action Perspective*; Addison-Wesley: Reading, MA, USA, 1978.
42. Huber, G.P. Organizational Learning: The Contributing Processes and the Literatures. *Organ. Sci.* **1991**, *2*, 88–115. [CrossRef]
43. Nonaka, I.; Takeuchi, H. *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation*; Oxford University Press: New York, NY, USA, 1995.
44. Makhloufi, L.; Laghouag, A.A.; Ali Sahli, A.; Belaid, F. Impact of Entrepreneurial Orientation on Innovation Capability: The Mediating Role of Absorptive Capability and Organizational Learning Capabilities. *Sustainability* **2021**, *13*, 5399. [CrossRef]
45. Iqbal, Q.; Piwowar-Sulej, K.; Agarwal, R.; Yaqub, M.Z. Sustainability-Oriented Leadership and Business Strategy: Examining the Roles of Procedural Environmental Justice and Job Embeddedness. *Bus. Strategy Environ.* **2025**, *34*, 2917–2933. [CrossRef]
46. Enbaia, E.; Alzubi, A.; Iyiola, K.; Aljuhmani, H.Y. The Interplay Between Environmental Ethics and Sustainable Performance: Does Organizational Green Culture and Green Innovation Really Matter? *Sustainability* **2024**, *16*, 10230. [CrossRef]
47. Boeske, J. Leadership towards Sustainability: A Review of Sustainable, Sustainability, and Environmental Leadership. *Sustainability* **2023**, *15*, 12626. [CrossRef]
48. Gorski, A.-T.; Ranf, D.E.; Badea, D.; Halmaghi, E.-E.; Gorski, H. Perspectives Concerning Leadership Research in the Framework of Corporate Sustainability. *J. Bus. Econ. Manag.* **2025**, *26*, 669–691. [CrossRef]
49. Aljuhmani, H.Y.; Emeagwali, O.L.; Ababneh, B. The Relationships between CEOs' Psychological Attributes, Top Management Team Behavioral Integration and Firm Performance. *Int. J. Organ. Theory Behav.* **2021**, *24*, 126–145. [CrossRef]
50. Almuammari, K.; Iyiola, K.; Alzubi, A.; Aljuhmani, H.Y. AI-Powered Insights: How Digital Supply Networks and Public–Private Alliances Shape Socio-Economic Paths to Sustainability. *Systems* **2025**, *13*, 691. [CrossRef]
51. Chen, Y.-S.; Lai, S.-B.; Wen, C.-T. The Influence of Green Innovation Performance on Corporate Advantage in Taiwan. *J. Bus. Ethics* **2006**, *67*, 331–339. [CrossRef]
52. Elkington, J. *Cannibals with Forks: The Triple Bottom Line of 21st Century Business*; New Society Publishers: Gabriola Island, BC, Canada; Stony Creek, CT, USA, 1998.
53. Cheah, J.S.S.; Ng, C.-H.; Fianto, B.A.; Teoh, A.P.; Gan, C.; Anisha, A.I.I.N. Green Innovation as a Strategic Imperative for Sustainable Business Performance: Evidence from Malaysian Industries during the COVID-19 Pandemic. *J. Clean. Prod.* **2024**, *470*, 143355. [CrossRef]
54. Hamad, O.; Alzubi, A.B.; Aljuhmani, H.Y. Entrepreneurial Competencies and Social Value Creation for Sustainable Economic Development: The Facilitating Roles of Comprehensive Social Competence and Technological Opportunism. *Sustainability* **2026**, *18*, 2530. [CrossRef]
55. Belkhir, A.Y.A.; Masaud, K.A.R. Effect of Transformation Leadership on Crisis Management in the Oil and Gas Sector in Libya. *Am. J. Econ. Bus. Innov.* **2024**, *3*, 12–17. [CrossRef]
56. Real, J.C.; Leal, A.; Roldán, J.L. Information Technology as a Determinant of Organizational Learning and Technological Distinctive Competencies. *Ind. Mark. Manag.* **2006**, *35*, 505–521. [CrossRef]
57. Walsh, J.P.; Ungson, G.R. Organizational Memory. *Acad. Manag. Rev.* **1991**, *16*, 57–91. [CrossRef]
58. Davenport, T.H.; Ronanki, R. Artificial Intelligence for the Real World. *Harv. Bus. Rev.* **2018**, *96*, 108–116.
59. Neiroukh, S.; Emeagwali, O.L.; Aljuhmani, H.Y. Artificial Intelligence Capability and Organizational Performance: Unraveling the Mediating Mechanisms of Decision-Making Processes. *Manag. Decis.* **2025**, *63*, 3501–3532. [CrossRef]
60. Kugara, G. AI-Augmented Decision-Making and Sustainability Performance in SMEs: A Hybrid PLS-SEM, ANN, and Multi-Group Analysis. *Ind. Manag. Data Syst.* **2026**, 1–24. [CrossRef]

61. Alegre, J.; Chiva, R. Assessing the Impact of Organizational Learning Capability on Product Innovation Performance: An Empirical Test. *Technovation* **2008**, *28*, 315–326. [CrossRef]
62. Camps, J.; Luna-Arocas, R. A Matter of Learning: How Human Resources Affect Organizational Performance. *Br. J. Manag.* **2012**, *23*, 1–21. [CrossRef]
63. Szulanski, G. Exploring Internal Stickiness: Impediments to the Transfer of Best Practice within the Firm. *Strateg. Manag. J.* **1996**, *17*, 27–43. [CrossRef]
64. Gomes, G.; Seman, L.O.; Berndt, A.C.; Bogoni, N. The Role of Entrepreneurial Orientation, Organizational Learning Capability and Service Innovation in Organizational Performance. *Rev. Gest.* **2021**, *29*, 39–54. [CrossRef]
65. Zhang, J.; Xu, H.; Xiao, X. The Role of Organizational Learning in Mediating the Relationship between Business Model Design and Innovation Performance. *Discret. Dyn. Nat. Soc.* **2022**, *2022*, 1317646. [CrossRef]
66. Mostepaniuk, A.; Nasr, E.; Awwad, R.I.; Hamdan, S.; Aljuhmani, H.Y. Managing a Relationship between Corporate Social Responsibility and Sustainability: A Systematic Review. *Sustainability* **2022**, *14*, 11203. [CrossRef]
67. Rihal, J.; Alzubi, A.; Aljuhmani, H.Y.; Berberoğlu, A. From Ethics to Ecology: How Ethical Leadership Drives Environmental Performance through Green Organizational Identity and Culture. *PLoS ONE* **2025**, *20*, e0336608. [CrossRef] [PubMed]
68. Edwards, J.R.; Lambert, L.S. Methods for Integrating Moderation and Mediation: A General Analytical Framework Using Moderated Path Analysis. *Psychol. Methods* **2007**, *12*, 1–22. [CrossRef] [PubMed]
69. Preacher, K.J.; Rucker, D.D.; Hayes, A.F. Addressing Moderated Mediation Hypotheses: Theory, Methods, and Prescriptions. *Multivar. Behav. Res.* **2007**, *42*, 185–227. [CrossRef] [PubMed]
70. Hayes, A.F. An Index and Test of Linear Moderated Mediation. *Multivar. Behav. Res.* **2015**, *50*, 1–22. [CrossRef] [PubMed]
71. Ageli, R.; Alzubi, A.B.; Aljuhmani, H.Y.; Iyiola, K. How and When Entrepreneurial Leadership Drives Sustainable Bank Performance: Unpacking the Roles of Employee Creativity and Innovation-Oriented Climate. *Sustainability* **2025**, *17*, 9259. [CrossRef]
72. Hair, J.F.; Sarstedt, M.; Ringle, C.M.; Gudergan, S.P. *Advanced Issues in Partial Least Squares Structural Equation Modeling*, 2nd ed.; SAGE Publications, Inc.: Thousand Oaks, CA, USA, 2024.
73. Hair, J.F.; Sarstedt, M.; Pieper, T.M.; Ringle, C.M. The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications. *Long Range Plan.* **2012**, *45*, 320–340. [CrossRef]
74. International Monetary Fund. *Libya: 2023 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Libya*; IMF Staff Country Reports; International Monetary Fund: Washington, DC, USA, 2023.
75. Dillman, D.A.; Smyth, J.D.; Christian, L.M. *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*, 4th ed.; Wiley: Hoboken, NJ, USA, 2014.
76. Meade, A.W.; Craig, S.B. Identifying Careless Responses in Survey Data. *Psychol. Methods* **2012**, *17*, 437–455. [CrossRef] [PubMed]
77. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E. *Multivariate Data Analysis*; Pearson Education Limited: Harlow, UK, 2013.
78. Tabachnick, B.G.; Fidell, L.S.; Ullman, J.B. *Using Multivariate Statistics*, 7th ed.; Pearson: New York, NY, USA, 2019.
79. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to Use and How to Report the Results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [CrossRef]
80. Baruch, Y.; Holtom, B.C. Survey Response Rate Levels and Trends in Organizational Research. *Hum. Relat.* **2008**, *61*, 1139–1160. [CrossRef]
81. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef] [PubMed]
82. Bliese, P.D. Within-Group Agreement, Non-Independence, and Reliability: Implications for Data Aggregation and Analysis. In *Multilevel Theory, Research, and Methods in Organizations: Foundations, Extensions, and New Directions*; Jossey-Bass/Wiley: Hoboken, NJ, USA, 2000; pp. 349–381.
83. Faul, F.; Erdfelder, E.; Buchner, A.; Lang, A.-G. Statistical Power Analyses Using G*Power 3.1: Tests for Correlation and Regression Analyses. *Behav. Res. Methods* **2009**, *41*, 1149–1160. [CrossRef] [PubMed]
84. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed.; Routledge: Hillsdale, NJ, USA, 1988.
85. Aguinis, H.; Beaty, J.C.; Boik, R.J.; Pierce, C.A. Effect Size and Power in Assessing Moderating Effects of Categorical Variables Using Multiple Regression: A 30-Year Review. *J. Appl. Psychol.* **2005**, *90*, 94–107. [CrossRef] [PubMed]
86. Shmueli, G.; Sarstedt, M.; Hair, J.F.; Cheah, J.-H.; Ting, H.; Vaithilingam, S.; Ringle, C.M. Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict. *Eur. J. Mark.* **2019**, *53*, 2322–2347. [CrossRef]
87. Brislin, R.W. Translation and Content Analysis of Oral and Written Materials. In *Handbook of Cross-Cultural Psychology: Methodology*; Allyn and Bacon: Boston, MA, USA, 1980; pp. 389–444.
88. Nunnally, J.C. *Psychometric Theory*, 2nd ed.; McGraw-Hill: New York, NY, USA, 1978.
89. Cao, G.; Duan, Y.; Li, G. Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis. *IEEE Trans. Eng. Manag.* **2015**, *62*, 384–395. [CrossRef]

90. Sarstedt, M.; Hair, J.F.; Cheah, J.-H.; Becker, J.-M.; Ringle, C.M. How to Specify, Estimate, and Validate Higher-Order Constructs in PLS-SEM. *Australas. Mark. J.* **2019**, *27*, 197–211. [CrossRef]
91. Edwards, J.R. Multidimensional Constructs in Organizational Behavior Research: An Integrative Analytical Framework. *Organ. Res. Methods* **2001**, *4*, 144–192. [CrossRef]
92. Law, K.S.; Wong, C.-S.; Mobley, W.H. Toward a Taxonomy of Multidimensional Constructs. *Acad. Manag. Rev.* **1998**, *23*, 741. [CrossRef] [PubMed]
93. Jarvis, C.B.; MacKenzie, S.B.; Podsakoff, P.M. A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *J. Consum. Res.* **2003**, *30*, 199–218. [CrossRef] [PubMed]
94. Weidner, K.; Nakata, C.; Zhu, Z. Sustainable Innovation and the Triple Bottom-Line: A Market-Based Capabilities and Stakeholder Perspective. *J. Mark. Theory Pract.* **2021**, *29*, 141–161. [CrossRef]
95. Crespo, N.F.; Roldan, L.B. Sustainable Innovation and Impact on Triple Bottom Line Performance: Are Innovation Types Simple Mediators? *Bus. Strategy Environ.* **2026**, *early view*. [CrossRef]
96. Hart, S.L. A Natural-Resource-Based View of the Firm. *Acad. Manag. Rev.* **1995**, *20*, 986–1014. [CrossRef]
97. Krara, W.; Alzubi, A.; Khadem, A.; Iyiola, K. The Nexus of Sustainability Innovation, Knowledge Application, and Entrepreneurial Success: Exploring the Role of Environmental Awareness. *Sustainability* **2025**, *17*, 716. [CrossRef]
98. Hussin, M.A.; Mohammad, S. SDG-Aligned Sustainable Performance in Hotels: Green Service Innovation, Eco-Innovation, and Environmental Management Accounting Under Stakeholder Pressure. *Sustainability* **2026**, *18*, 9773. [CrossRef]
99. Becker, J.-M.; Klein, K.; Wetzels, M. Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models. *Long Range Plan.* **2012**, *45*, 359–394. [CrossRef]
100. Kock, N. Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. *Int. J. e-Collab. IJeC* **2015**, *11*, 1–10. [CrossRef]
101. Harman, H.H. *Modern Factor Analysis*, 3rd ed. revised; University of Chicago Press: Chicago, IL, USA, 1976.
102. Podsakoff, P.M.; MacKenzie, S.B.; Podsakoff, N.P. Sources of Method Bias in Social Science Research and Recommendations on How to Control It. *Annu. Rev. Psychol.* **2012**, *63*, 539–569. [CrossRef] [PubMed]
103. Gaskin, J.E.; Lowry, P.B.; Rosengren, W.; Fife, P.T. Essential Validation Criteria for Rigorous Covariance-Based Structural Equation Modelling. *Inf. Syst. J.* **2025**, *35*, 1630–1661. [CrossRef]
104. Ringle, C.M.; Wende, S.; Becker, J.-M. *SmartPLS 4*; SmartPLS: Oststeinbek, Germany, 2022.
105. Henseler, J.; Hubona, G.; Ray, P.A. Using PLS Path Modeling in New Technology Research: Updated Guidelines. *Ind. Manag. Amp Data Syst.* **2016**, *116*, 2–20. [CrossRef]
106. Hu, L.; Bentler, P.M. Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives. *Struct. Equ. Model. Multidiscip. J.* **1999**, *6*, 1–55. [CrossRef]
107. Kenny, D.A. Moderation. Available online: https://davidakenny.net/cm/moderation.htm (accessed on 5 October 2026).
108. Nitzl, C.; Roldan, J.L.; Cepeda, G. Mediation Analysis in Partial Least Squares Path Modeling: Helping Researchers Discuss More Sophisticated Models. *Ind. Manag. Data Syst.* **2016**, *116*, 1849–1864. [CrossRef]
109. Zhao, X.; Lynch, J.G., Jr.; Chen, Q. Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *J. Consum. Res.* **2010**, *37*, 197–206. [CrossRef]
110. Becker, J.-M.; Ringle, C.M.; Sarstedt, M. Estimating Moderating Effects in PLS-SEM and PLSc-SEM: Interaction Term Generation*data Treatment. *J. Appl. Struct. Equ. Model.* **2018**, *2*, 1–21. [CrossRef] [PubMed]
111. Hayes, A.F. *Introduction to Mediation, Moderation, and Conditional Process Analysis, Second Edition: A Regression-Based Approach*, 2nd ed.; The Guilford Press: New York, NY, USA; London, UK, 2017.
112. Muthén, B.O.; Satorra, A. Complex Sample Data in Structural Equation Modeling. *Sociol. Methodol.* **1995**, *25*, 267–316. [CrossRef] [PubMed]
113. Moulton, B.R. An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units. *Rev. Econ. Stat.* **1990**, *72*, 334–338. [CrossRef]
114. Hair, J.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling*, 3rd ed.; SAGE Publications, Inc.: Los Angeles, CA, USA, 2021.
115. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
116. Henseler, J.; Ringle, C.M.; Sarstedt, M. A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
117. Franke, G.; Sarstedt, M. Heuristics versus Statistics in Discriminant Validity Testing: A Comparison of Four Procedures. *Internet Res.* **2019**, *29*, 430–447. [CrossRef]
118. Hair, J.F.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M.; Danks, N.P.; Ray, S. Moderation Analysis. In *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*; Hair, J.F., Jr., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 155–172.

119. Shmueli, G.; Ray, S.; Velasquez Estrada, J.M.; Chatla, S.B. The Elephant in the Room: Predictive Performance of PLS Models. *J. Bus. Res.* **2016**, *69*, 4552–4564. [CrossRef]
120. Hair, J.F.; Sabol, M.; Islam, M.S.; Murshed, F. Conditional Mediation (CoMe) Models with PLS-SEM: An Update, Review, and Best-Practice Recommendations. *Australas. Mark. J.* **2026**, *34*, 178–191. [CrossRef]
121. Kriym, A.; Aljuhmani, H.Y. Knowledge Management in Environmental Sustainability: The Roles of Financial and Social Integration. *Sustainability* **2026**, *18*, 735. [CrossRef]
122. Saed, H.; Snene Manzli, Y.; Jeribi, A.; Alnafisah, H. Analyzing Blockchain Adoption in Management Operations through an Extended UTAUT Model in the Libyan Context. *Sci. Rep.* **2025**, *15*, 31107. [CrossRef] [PubMed]
123. Akerele, T.M.; Owoigbe, K.V.; Idowu, R.L. Geoinformatics and Smart Marine Asset Management: Technological Advancements, Economic Impact, Environmental Benefits, and Strategic Decision-Making in Africa's Oil & Gas Sector. *Int. J. Res. Publ. Rev.* **2025**, *6*, 1841–1849. [CrossRef]
124. Eisenhardt, K.M.; Graebner, M.E. Theory Building from Cases: Opportunities And Challenges. *Acad. Manag. J.* **2007**, *50*, 25–32. [CrossRef]

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