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Top Management Support and Project Performance: Parallel Mediation through AI Adoption and Environmental Responsiveness

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***Abstract*— Project performance shortfalls persist in Malaysia's oil and gas sector, implying executive support improves outcomes only when it activates enabling capabilities. Using TOE (with RBV and DOI support), this study tests whether top management support (TMS) influences project performance (PP) indirectly through parallel mediation via AI adoption (AIA) and environmental responsiveness (ER). Survey data from 412 professionals were analyzed using PLS-SEM with bootstrapping. TMS significantly increases AIA and ER; AIA significantly improves PP, while ER shows a marginal effect. The direct TMS→PP relationship is not significant, but the total indirect effect is significant, indicating indirect-only mediation. The findings clarify how executive support translates into performance through digital and adaptive capabilities; practically, leaders should operationalize support via AI governance and investment, alongside routines to sense and respond to regulatory and stakeholder pressures.**

Keywords— ***Top management support; Project performance; AI adoption; Environmental responsiveness; Malaysia oil and gas.***

I. INTRODUCTION

1.1. Research problem, motivation, and gap

Project performance remains a persistent concern in capital- intensive, high-risk sectors, where schedule slippage, cost escalation, and quality deviations quickly translate into significant financial and operational consequences. In Malaysia's oil and gas projects, underperformance is often linked to execution complexity and "5M" resource constraints (manpower, money, machines, methods, and materials) that destabilize delivery and cost control (Roshdi et al., 2023). These operational challenges are compounded by energy- transition and decarbonization expectations, which raise governance demands and intensify stakeholder scrutiny of project organizations (Government of Malaysia, 2023; PETRONAS, 2023a).

Top management support (TMS) is widely recognized as a strategic driver of project success because it legitimizes priorities, mobilizes resources, and aligns actors behind project goals. However, evidence suggests its influence is not consistently direct; TMS improves outcomes only when translated into capabilities and routines that strengthen execution and adaptation across the project lifecycle (Fareed & Su, 2022; Zwikael, 2008). Two enabling capabilities are especially relevant: AI adoption (AIA), which can enhance planning accuracy, risk sensing, decision support, and process efficiency, but depends on readiness, governance, and integration quality rather than technology presence alone (Adamantiadou & Tsironis, 2025; Merhi, 2023); and environmental responsiveness (ER), which reflects disciplined organizational responses to regulatory and stakeholder pressures under tighter environmental and sustainability expectations (Aragón-Correa & Sharma, 2003; Hart, 1995; Government of Malaysia, 2023; PETRONAS, 2023a).

Despite broad agreement that TMS matters, the literature provides limited explanation of how executive support becomes performance-enhancing under simultaneous digital transformation demands and rising environmental stakeholder pressure. This study addresses that mechanism gap by modelling AI adoption and environmental responsiveness as parallel mediating capabilities linking TMS to project performance in Malaysia's oil and gas projects. The proposed relationships are conceptually informed by TOE, RBV, and DOI, which are developed in the theoretical foundation section.

1.2 Research objective and research questions

This study examines whether top management support improves project performance through parallel mediation by AI adoption and environmental responsiveness in Malaysia's oil and gas project context. Two research questions guide the study:

1. Does top management support enhance AI adoption and environmental responsiveness in oil and gas project organizations?
2. Do AI adoption and environmental responsiveness mediate the relationship between top management support and project performance, and how do their mediation effects compare?

1.3 Contributions

This study makes three contributions:

1. Theoretical: Explains the TMS–performance relationship primarily as a capability-building mechanism through dual pathways (AIA and ER), integrating TOE, RBV, and DOI.
2. Methodological: Tests parallel mediation in a single structural model, enabling comparison of indirect effects.
3. Contextual/practical: Provides Malaysia oil & gas–specific guidance on translating executive "support" into AI enablement and structured responsiveness routines under transition pressures (Government of Malaysia, 2023; PETRONAS, 2023a; Roshdi et al., 2023).

2. Theoretical Foundation And Hypotheses

2.1 Integrating RBV, TOE, and DOI to explain performance transmission

This study develops a mechanism-based explanation of how top management support (TMS) translates into project performance (PP) in Malaysia's oil and gas project context through two parallel capability channels: AI adoption (AIA) and environmental responsiveness (ER). Rather than assuming that executive support directly improves cost, schedule, quality, and stakeholder outcomes, the model argues that TMS becomes performance-relevant mainly when it is converted into routinised organizational capabilities that shape day-to- day project execution.

First, the resource-based view (RBV) clarifies why TMS is rarely performance-relevant as a "standalone" condition. RBV explains that resources generate value when they are deployed through firm capabilities and practices that enable reliable execution and advantage [1], [2]. In this study, TMS is conceptualized as an enabling strategic resource (e.g., authority, governance discipline, escalation rights, and resource mobilization capacity) whose value is realized when it is operationalized into execution capabilities that alter project control cycles and decisions.

Second, the Technology–Organization–Environment (TOE) framework specifies that technology outcomes and downstream performance are shaped jointly by organizational conditions and environmental forces [3]. This is especially relevant in oil and gas projects where delivery performance depends on internal execution quality and external fit with regulators, stakeholders, and supply-chain constraints. TOE therefore supports a dual capability pathway expectation: TMS can transmit performance effects through a technology- enabled capability (AIA) and an environment-facing adaptive capability (ER) in parallel.

Third, Diffusion of Innovations (DOI) explains how leadership accelerates adoption and routinization of innovations via legitimization, uncertainty reduction, and resource allocation [4]. In project-based work, this diffusion-and-routinization step is critical because digital tools typically improve outcomes only when embedded into planning, reporting, risk management, and decision cycles.

Contribution: By integrating RBV – TOE – DOI, this study specifies why TMS needs capability conversion (RBV), where parallel capability channels arise (TOE), and how adoption becomes routinised (DOI), motivating a parallel mediation structure: TMS → (AIA, ER) → PP.

2.2 Top management support and project performance

TMS is widely recognized as an important success condition in project environments because executives shape resource prioritization, governance discipline, and cross-functional coordination [5]. However, RBV implies that TMS is most impactful when translated into operational routines and capabilities rather than remaining symbolic [1], [2].
Accordingly, a positive baseline relationship is expected, while stronger explanatory power is anticipated through the two capability channels.
H1: Top management support has a positive effect on project performance.

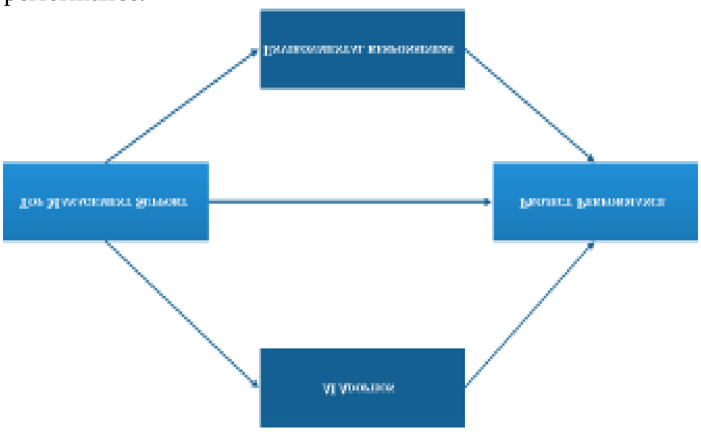


FIGURE I. SUMMARIZES THE PROPOSED PARALLEL MEDIATION MODEL

2.3 AI adoption as a capability pathway linking top management support and project performance

In this study, AI adoption (AIA) is treated as a technology- enabled organizational capability, emphasizing implementation and embedding of AI-supported routines into project planning, monitoring/control, and decision-making. DOI predicts that TMS accelerates AIA by legitimizing the innovation, reducing perceived risk, sponsoring pilots, and enabling learning needed for routinization [4]. TOE complements this logic by highlighting readiness conditions (resources, governance, skills, and fit with environmental demands) that are materially shaped by executive support [3]. Empirical AI-adoption research reinforces that sustained value typically depends on organizational readiness and the capability-building journey from pilots to operationalization [6].

From an RBV-compatible capability perspective, AIA yields performance benefits when it improves the quality and speed of project decisions and controls (e.g., forecasting, anomaly detection, and risk analytics). Evidence on AI capability indicates positive links to organizational outcomes and performance-relevant benefits when AI is developed as an organizational capability rather than an isolated tool [7]. Project-level AI research similarly indicates that AI tools can enhance project management functions and decision support when appropriately integrated into project routines [8]. Therefore, TMS is expected to strengthen AIA, and AIA is expected to improve PP; consistent with capability-conversion logic, AIA is expected to mediate TMS → PP.

H2: Top management support has a positive effect on AI adoption.

H3: AI adoption has a positive effect on project performance.

H4: AI adoption mediates the relationship between top management support and project performance.

2.4 Environmental responsiveness as a capability pathway linking top management support and project performance

Environmental responsiveness (ER) reflects the organization's capability to sense, interpret, and respond rapidly to external pressures (regulatory changes, stakeholder expectations, supply disruptions, and volatility). TOE positions environmental forces as central to organizational outcomes, implying that performance depends on both execution and external alignment [3]. RBV and dynamic capability logic further indicate that adaptive capabilities protect performance under turbulence by enabling sensing, timely reconfiguration, and coordinated response [2]. In project ecosystems, stakeholder-facing governance and relationship conditions are consistently associated with performance-relevant outcomes, including trust and acceptance dynamics [9], while sustainability-oriented project work highlights the performance relevance of stakeholder engagement and external alignment mechanisms [10].

ER operationalization (single sentence): Consistent with this study's measurement intent, ER is operationalized as routinised, executive-enabled practices such as structured stakeholder engagement, rapid escalation/change-control, and compliance alignment mechanisms that shorten sensing–response cycles.

Thus, TMS is expected to strengthen ER, ER is expected to enhance PP, and ER is expected to mediate TMS → PP.

H5: Top management support has a positive effect on environmental responsiveness.

H6: Environmental responsiveness has a positive effect on project performance.

H7: Environmental responsiveness mediates the relationship between top management support and project performance.

II. METHOD

3.1 Research design and sample

This study employed a quantitative, cross-sectional survey design to test the proposed relationships among top management support (TMS), AI adoption (AIA), environmental responsiveness (ER), and project performance (PP). A cross-sectional approach is appropriate for theory testing where the objective is to examine associations among latent constructs in a defined context at a single point in time [11]. The unit of analysis is the individual professional involved in oil and gas project environments in Malaysia.

A purposive sampling strategy was used to target respondents who could provide informed assessments of managerial support, technology adoption practices, environmental responsiveness routines, and project performance outcomes within their organizations. Respondents were included if they: (i) were oil and gas professionals, (ii) were employed by oil and gas companies operating in Malaysia, (iii) had at least two years of experience in the oil and gas industry, (iv) were directly or indirectly involved in project work (e.g., EPC, operations, maintenance, engineering, or project delivery roles), and (v) held positions with adequate exposure to organizational practices and project execution (e.g., project managers, engineers, supervisors, team leaders, or equivalent roles).

Data collection was conducted over a one-month period using both electronic distribution and physical circulation of questionnaires to maximize reach and participation. • To mitigate evaluation apprehension and encourage candid responses, participation was voluntary and anonymous, and respondents were informed that there were no right or wrong answers and that responses would be used only for academic purposes, consistent with recommended survey design practices [12]. After screening for completeness and eligibility, 412 usable responses were retained for analysis.

3.2 Measures and instrument development

Data were collected using a structured questionnaire comprising two sections: (i) respondent background information (e.g., role, experience, and organisational context), and (ii) measurement items for the study constructs. All focal constructs were operationalized using multi-item reflective measures on a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree). Items were adapted from established measures in the project management, innovation adoption, and environmental strategy literatures, with wording refined to fit the Malaysian oil and gas project setting while preserving the original construct meaning [13], [14]. Because the indicators represent manifestations of their respective latent constructs and are expected to covary, reflective measurement was deemed appropriate for all focal variables [15].

- Top management support (TMS) was measured with 7 items, capturing senior management commitment, resource provision, strategic direction, and involvement in enabling project success (e.g., “Top management provides adequate resources for project success”). Consistent with project governance and executive support literature, TMS reflects the extent to which top leaders actively enable project delivery [16].
- AI adoption (AIA) was measured with 7 items, reflecting organizational use of AI-enabled tools and practices for decision-making, automation, analytics, and operational improvements (e.g., “Our organization uses AI tools to support decision- making”). This aligns with diffusion and organizational adoption research in which adoption is reflected in actual use and routinization of AI-related applications [17], [18].
- Environmental responsiveness (ER) was measured with 7 items, capturing an organisation’s capability to sense, interpret, and respond to regulatory, stakeholder, and ecological demands affecting projects (e.g., “Environmental responsiveness is integrated into project decision-making”). This reflects capability-based views of proactive environmental strategy and responsiveness to external pressures [19], [20].
- Project performance (PP) was measured with 9 items, reflecting multidimensional project outcomes (e.g., schedule, cost, quality, and stakeholder outcomes). This is consistent with the view that project success/performance is multidimensional rather than purely time–cost–quality based [21].

Prior to full data collection, the instrument underwent pilot testing to assess clarity, face validity, and preliminary reliability. Minor refinements were made to ensure item wording was context-appropriate and unambiguous. This pilot process supported the content clarity and interpretability of the adapted items, consistent with instrument development guidance [13], [14].

3.3 Data screening, common method bias, and analytical procedure (PLS-SEM)

Preliminary data screening was conducted to ensure suitability for multivariate analysis. Missing data were checked, and response patterns were inspected for irregularities. Multivariate outliers were assessed using Mahalanobis distance criteria consistent with multivariate screening recommendations [22]. Normality diagnostics (skewness and kurtosis) were also reviewed; however, strict multivariate normality is not a prerequisite for variance-based SEM, supporting the suitability of PLS-SEM [15].

Given that all measures were collected via a single survey instrument, steps were taken to mitigate and assess common method bias (CMB). Procedural remedies were incorporated in the questionnaire design (e.g., clear instructions, reduction of ambiguity, and separation of construct blocks where feasible), consistent with recommended practices [12]. Statistically, Harman’s single-factor test was applied as an initial diagnostic, with additional attention to collinearity-based checks where appropriate in PLS-SEM settings [23]. In line with collinearity-based CMB assessment guidance, full collinearity VIF values were examined to ensure they did not indicate problematic common method variance [23].

Hypotheses were tested using partial least squares structural equation modelling (PLS-SEM) implemented in SmartPLS. PLS-SEM is appropriate when the research objective prioritizes prediction and explanation of variance in key endogenous constructs, and when models include mediation paths and multiple constructs [15]. The analysis followed a two-stage procedure: (i) assessment of the measurement model, and (ii) assessment of the structural model.

Measurement model evaluation examined:

1. Indicator reliability via outer loadings (preferred $\geqslant$ .70);
2. Internal consistency reliability using composite reliability (CR $\geqslant$ .70);
3. Convergent validity using average variance extracted (AVE $\geqslant$ .50) [24], [15]; and
4. Discriminant validity using the HTMT criterion [25].

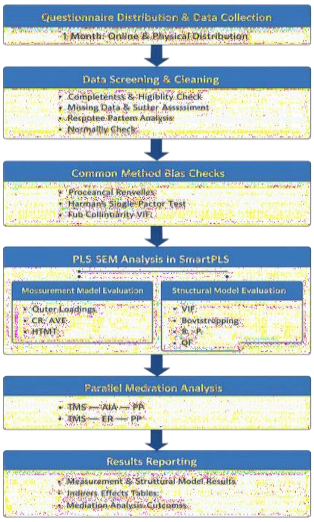
Structural model evaluation included:

1. Collinearity assessment using variance inflation factors (VIF) to ensure predictor constructs did not exhibit problematic multicollinearity [15];
2. Path coefficient estimation and hypothesis testing using bootstrapping to obtain robust standard errors, t-values, and confidence intervals;
3. Explanatory power using R^2 for endogenous constructs; and
4. Effect size using f^2 to evaluate each predictor’s contribution [26], [15]. Predictive relevance (Q^2)

was also considered where appropriate to evaluate out-of- sample predictive capability in line with PLS-SEM reporting expectations [15].

Parallel mediation testing was conducted by estimating the specific indirect effects of TMS on PP through (i) AIA and (ii) ER. The significance of mediation was determined using bootstrapped indirect effects and confidence intervals, consistent with contemporary mediation testing standards in SEM [15].

<u>Data Analysis Flow for PLS-SEM</u>



III. RESULTS AND DISCUSSION

4.1 Respondent profile

A total of 412 usable responses from Malaysia's oil and gas professionals were analyzed using PLSSEM (SmartPLS). The sample was predominantly male (70.4%), largely within the 36–55 age range (78.9%), and highly educated (84.2% bachelor's degree or higher). Most respondents were in middle management (69.4%) and reported 11–20 years of work experience (67.0%), indicating strong exposure to organizational practices and project execution.

4.2 Measurement model assessment (focal constructs: TMS, AIA, ER, PP)

The measurement model was evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity for the focal constructs: Top Management Support (TMS), AI Adoption (AIA), Environmental Responsiveness (ER), and Project Performance (PP).

4.1.1 Indicator reliability

Outer loadings were acceptable overall. Loading ranges were 0.726–0.817 (TMS), 0.729–0.825 (AIA), 0.684–0.815 (ER), and 0.664–0.776 (PP). Two indicators were slightly below 0.70 (ER1 = 0.684; PP7 = 0.664) but were retained because overall reliability and convergent validity were satisfactory.

4.1.2 Internal consistency reliability and convergent validity

All focal constructs exceeded recommended thresholds. Cronbach's alpha ranged from 0.878 to 0.898, composite reliability (CR) ranged from 0.905 to 0.917, and AVE ranged from 0.552 to 0.605, supporting internal consistency and convergent validity.

TABLE I. MEASUREMENT MODEL SUMMARY (FOCAL CONSTRUCTS)

Construct	**Items**	**Loading range (min–max)**	**Cronbach' α**	**rho_A**	**CR**	**AVE**
AIA	7	0.729–0.825	0.887	0.892	0.912	0.597
ER	7	0.684–0.815	0.878	0.883	0.905	0.578
PP	9	0.664–0.776	0.898	0.902	0.917	0.552
TMS	7	0.726–0.817	0.892	0.898	0.915	0.605

4.1.3. Discriminant validity (HTMT)

Discriminant validity was supported using HTMT. All HTMT values among the focal constructs were well below conservative thresholds.

TABLE II. HTMT RATIO

	AIA	**ER**	**PP**	**TMS**
AIA	—	0.333	0.391	0.383
ER	0.333	—	0.341	0.364
PP	0.391	0.341	—	0.359
TMS	0.383	0.364	0.359	—

4.3. Structural model results and hypothesis testing

4.3.1 Collinearity assessment (VIF)

Collinearity was not a concern. VIF values for the focal structural paths were within acceptable bounds (e.g., TMS→AIA = 1.354, TMS→ER = 1.354, AIA→PP = 1.285, ER→PP = 1.317, TMS→PP = 1.413).

4.3.2 Explanatory and predictiv power (R^2 and Q^2_ predict*) Q^2_ predict) Q^2_ predict) Q^2_ predict)*

The model explained meaningful variance in the endogenous constructs: $R^2 = 0.213$ (AIA), $R^2 = 0.232$ (ER), and $R^2 = 0.264$ (PP). Predictive relevance was also supported (Q^2_predict > 0): **0.184 (AIA), 0.204 (ER), and 0.211 (PP).**

TABLE III. EXPLAINED VARIANCE AND PREDICTIVE RELEVANCE

Endogenous construct	R^2	R^2 adjusted	Q^2_predict
AIA	0.213	0.203	0.184
ER	0.232	0.222	0.204
PP	0.264	0.251	0.211

3.3 Direct effects (H1–H5)

Bootstrapping results indicated that TMS significantly increased AIA and ER, and AIA significantly improved PP. The direct effect TMS→PP was not statistically significant. The path ER→PP was marginal (p = 0.061) not significant at the 5% level but indicative at the 10% level.

TABLE IV. DIRECT EFFECTS AND EFFECT SIZES (F^2)

Hypothesis / Path	β	t-value	p-value	f^2	Decision
H1: TMS → PP	0.082	1.734	0.083	0.006	Not supported
H2: TMS → AIA	0.171	3.394	0.001	0.028	Supported
H3: AIA → PP	0.165	3.465	0.001	0.029	Supported
H4: TMS → ER	0.145	2.700	0.007	0.020	Supported
H5: ER → PP	0.093	1.873	0.061	0.009	Not supported (marginal at 10%)

4.4. Parallel mediation results (H6–H7)

Parallel mediation was assessed using bootstrapped indirect effects. Consistent with the structural results, the direct path from TMS to PP was not statistically significant (β = 0.082, p = 0.083), while TMS significantly predicted both mediators (TMS→AIA: β = 0.171, p = 0.001; TMS→ER: β = 0.145, p = 0.007). This pattern supports indirect-only mediation, indicating that top management support influences project performance primarily through capability-building mechanisms rather than through a direct pathway.

TABLE V. INDIRECT (MEDIATION) EFFECT

Indirect path	Indirect effect (β)	t-value	p-value	Interpretation
H6/H7 (Total): TMS → (AIA, ER) → PP	0.042	2.733	0.006	Significant indirect effect; indirect-only pattern

5. Discussion

5.1 Summary of key findings

This study examined whether top management support (TMS) improves project performance (PP) directly and indirectly through two parallel capability pathways: AI adoption (AIA) and environmental responsiveness (ER). The results show three clear patterns. First, TMS did not have a significant direct effect on PP (β = 0.082, p = 0.083). This suggests that executive commitment, by itself, may not translate into improved project outcomes unless it is converted into execution-relevant capabilities and routines consistent with evidence that top management involvement affects project success primarily when it is operationalized through concrete support practices and governance routines rather than remaining symbolic [27]. Second, TMS significantly increased both AIA and ER (TMS→AIA: β = 0.171, p = 0.001; TMS→ER: β = 0.145, p = 0.007), indicating that managerial commitment is strongly linked to building organizational readiness and capability deployment. This aligns with technology adoption perspectives: organizational context and environmental context shape adoption outcomes (TOE), and managerial legitimization and resource sponsorship accelerate diffusion and routinization (DOI) [28]–[30]. Third, the capability-to-performance links were asymmetric: AIA had a significant positive effect on PP (β = 0.165, p = 0.001), whereas ER showed only a marginal association with PP (β = 0.093, p = 0.061). Importantly, the total indirect effect of TMS on PP through the parallel mediators was significant (β = 0.042, p = 0.006), supporting an indirect-only mediation pattern. Conceptually, this indicates that TMS influences PP primarily through capability building particularly via AI adoption rather than through a direct pathway.

5.2 Theoretical implications

Capability-activation explanation of TMS → PP. The finding that TMS does not significantly predict PP directly, but does predict PP indirectly through capability pathways, strengthens a mechanism-based interpretation of managerial influence. From an RBV standpoint, top management support constitutes a strategic organizational resource that becomes performance-relevant only when it is transformed into valuable capabilities and routines [31]. Thus, executive commitment matters most when it is converted into governance discipline, digital routines, and systematic operational practices rather than being expressed only as intent or high-level endorsement.

Clarifying TOE's "dual pathway" logic in performance models. The integrated framing is consistent with the TOE argument that technology-related outcomes are shaped by organizational conditions and environmental pressures [28], [30]. By modelling AI adoption (technology-enabled capability) and environmental responsiveness (environment-facing capability) in parallel, this study extends TOE usage beyond adoption-only models and positions TOE as a mechanism framework explaining performance transmission through complementary capability channels in project settings where delivery depends on both internal execution capacity and external fit (regulatory/stakeholder constraints) [28], [30].

DOI and the routinization of AI as the stronger transmission mechanism. The stronger AIA→PP relationship supports DOI's logic that performance effects emerge when innovations move from awareness/pilots into routinised use [29]. In project environments, AI adoption embedded into planning, forecasting, monitoring, and decision routines can reduce variance and improve control quality—consistent with systematic evidence on AI applications across core project tasks (e.g., cost estimation, schedule forecasting, risk assessment) [32]. This also aligns with AI capability research arguing that AI becomes valuable when it forms a capability system (data, analytics routines, skills, governance) rather than isolated tools [33].

Interpreting the weaker ER → PP path. ER's marginal association with PP can be interpreted in several non-exclusive ways. First, responsiveness may function as a risk-prevention capability whose impact is more visible in avoidance of failures (compliance breaches, stakeholder disputes, regulatory delays) than in immediate performance gains—an effect that is harder to detect in cross-sectional designs. Second, in mature and tightly regulated environments, baseline environmental responsiveness may already be institutionalized, reducing variance and weakening observable performance effects. Third, ER may influence PP indirectly through intermediate mechanisms such as reduced conflict, stronger legitimacy, or fewer disruptions—consistent with capability-based environmental strategy perspectives and the natural-resource-

based view logic [34], [35]. Future models may capture ER effects more clearly using multistage pathways or longitudinal indicators.

5.3 Practical implications

Operationalize TMS through AI enablement and adoption governance. Because AI adoption is the stronger capability pathway linked to project performance, executive teams should translate "support" into tangible adoption enablers: (i) dedicated funding for data infrastructure and AI-enabled tools,

(ii) clear governance structures for AI use (standards, accountability, ethics, and risk controls), (iii) training and upskilling plans aligned to project processes, and (iv) change sponsorship that encourages routinised usage rather than isolated experimentation. This is consistent with evidence that leadership commitment and organizational factors are critical to AI implementation success [37].

Build "project-level AI routines," not only "AI projects." To improve performance, AI should be embedded into recurring project routines: schedule forecasting, cost monitoring, risk sensing, procurement analytics, and exception escalation. The objective is not AI adoption as a symbolic digitalization indicator, but AI as a repeatable operational capability that supports decision speed and accuracy [33].

Strengthen environmental responsiveness as a disciplined routine. Although ER's path to PP is weaker in this model, the significant TMS→ER path indicates that leaders can meaningfully shape responsiveness capability. Practically, organizations should routinise sensing and response through structured monitoring of regulatory changes, stakeholder engagement protocols, and early-warning mechanisms that reduce compliance and disruption risks consistent with proactive environmental capability arguments [34], [35]. A key managerial message follows: "Support" must be capability-based executive attention should be evaluated by whether it produces (i) AI adoption embedded in processes and (ii) responsiveness routines embedded in governance.

5.4 Limitations and future research

This study has limitations that provide directions for future research. (1) Cross-sectional design: the study captures relationships at a single time point; causal dynamics and time- lagged effects especially for ER may be better assessed using longitudinal designs. (2) Single-source survey data: common method concerns are possible; future research may triangulate with objective performance indicators (schedule variance, cost variance, NCRs) or multi-source responses (project managers and executives). Methodological guidance recommends

procedural remedies and statistical assessment in such contexts [36]. (3) Context specificity: the findings are grounded in Malaysia's oil and gas professional context; replication across other project-based sectors (construction, utilities, infrastructure) and regions would strengthen generalizability.

(4) Richer mediation structures: future studies could examine sequential mediation (e.g., TMS → AIA → operational analytics capability → PP) or moderated mediation (e.g., project complexity, environmental turbulence, digital maturity) to explain when ER becomes more performance- relevant [28], [30], [35].

IV. CONCLUSIONS

This study examined how top management support (TMS) translates into project performance (PP) in Malaysia’s oil and gas project environment by testing two parallel capability pathways: AI adoption (AIA) and environmental responsiveness (ER). Using survey data from 412 professionals and PLS-SEM, the results indicate that TMS does not significantly improve PP through a direct pathway. Instead, TMS operates primarily through capability activation: TMS significantly strengthens both AIA and ER, and AIA has a significant positive effect on PP, whereas ER shows only a marginal association with PP. Importantly, the combined indirect effect of TMS on PP via AIA and ER is significant, supporting an indirect-only mediation pattern. Overall, the findings imply that executive support becomes performance- relevant when it is operationalized into routinised organizational capabilities most notably AI-enabled routines that enhance forecasting, monitoring, and decision quality.

The study contributes by clarifying why leadership support alone may be insufficient in complex project settings unless it is translated into capability-building investments and governance routines. Practically, executives should evaluate “support” by whether it produces implementable adoption conditions AI governance, funding, data readiness, process integration, and skills development so AI use becomes embedded in recurring project controls. Although ER’s performance effect is weaker, the significant TMS→ER relationship indicates that leaders can still strengthen responsiveness through disciplined sensing-and-response routines (e.g., structured stakeholder engagement, compliance alignment, and rapid escalation/change control) that reduce disruption risks.

Limitations include the cross-sectional design and single-source survey data, which may under-capture time-lagged effects, particularly for ER. Future studies should use longitudinal designs, triangulate with objective performance indicators (e.g., schedule/cost variance), and test richer mechanisms (e.g., sequential mediation) and boundary conditions (e.g., project complexity, environmental turbulence, and digital maturity) to clarify when ER becomes more performance-relevant and when AI adoption yields the strongest performance gains.

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