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**Article**

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# When Does AI Capability Pay Off in SMEs? Strategic decision quality and top management support in a moderated mediation model

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## Abstract

Artificial intelligence (AI) capability is increasingly treated as a strategic resource, yet small and medium-sized enterprises (SMEs) often obtain uneven returns from similar AI investments. We explain this variation by focusing on how AI-enabled information is converted into strategic judgment and organizational performance. Drawing primarily on organizational information processing theory (OIPT), we propose that AI capability improves strategic decision quality, which in turn enhances SME business performance. We further argue that top management support strengthens both the conversion of AI capability into decision quality and the conversion of decision quality into performance, producing a dual-stage moderated mediation process. Consistent with the final research design, AI capability and top management support are measured at T1, strategic decision quality at T2, and SME business performance at T3, with waves separated by three months. Results of this study indicated that all hypotheses were significantly supported. This study provided a significant mediation role of strategic decision quality in the relationship between AI capability and SME performance. In addition, moderation effect of TMS was significant at three level of study. The study contributes by reframing AI value creation as an information-processing and managerial implementation problem rather than a technology-possession effect.

***Keywords:*** Artificial Intelligence Capability; Strategic Decision Quality; Top Management Support; SME Performance; Organizational Information Processing Theory

## 1. Introduction

Although artificial intelligence is becoming increasingly accessible to small and medium-sized enterprises (SMEs), access does not necessarily generate equivalent value [1]. Firms may invest comparable resources in data, software, and AI expertise yet achieve markedly different outcomes [1]. This disparity raises a critical strategic question that extends beyond the scope of technology-adoption research: How do AI capabilities translate into superior firm performance, and under what conditions is this performance potential most likely to be realized? These companies have more limited budgets, fewer experts and are more reliant on a few key decision makers. In this context, the use of AI might not be a substitute for managerial judgment so much as an enhancement to the information at managers' disposal. While AI tools can pull data together, uncover patterns and assess options, it is up to managers to determine which signals are relevant and what actions require limited resources [2].

Existing studies have associated AI ability to decision-making results and company performance [3,4], however there are lots of important questions. There are many studies that consider that AI capability leads to performance itself, without also elucidating the decision process. Leadership is also frequently mentioned as a broad positive influence but the reason why the managerial support influences the value of AI-enabled information is not explained [5]. Moreover, cross sectional designs make it challenging to isolate the ability to do AI, the quality of the decision, and the performance in time. These constraints limit our understanding on the mechanisms that explain the different outcomes of similar investments in AI.

We tackle these challenges by creating a model of AI value creation from information processing. The main thesis is the ability to derive value from AI increases the firm's ability to acquire, integrate, and analyze information [6]. Strategic decision quality refers to how well managers translate the ability into good decision making, and how good decisions enhance performance by leveraging limited resources to better options [7]. The boundary condition that

supports both stages is top management support, which means it legitimizes and resources the use of AI before a decision is made, and it mobilizes coordination and resources after a decision is made.

The key theoretical framework is Organizational Information Processing Theory (OIPT). Organizations do better when the uncertainty and complexity they encounter is matched by their information-processing capacity [8,9]. This reasoning can be directly applied to the proposed model. The ability of the organisation to process information through AI expands its information processing capacity [10]. The quality of managerial processing of information is a component of strategic decision quality [11], and top management support aids in the integration of information into managerial decisions, and in the implementation of managerial decisions [12]. The study thus moves from the question of who's got the better technology to the question of who's converting the information better, and why managerial support makes a difference to that process.

## 2. Theory and Hypothesis Development

### 2.1 **Organizational Information Processing Theory**

Organizational Information Processing Theory begins with the idea that uncertainty creates information-processing requirements. As markets, technologies, and competitive conditions become more complex, firms need stronger capacity to collect, interpret, share, and use information [8,9]. Organizations respond by developing systems, roles, routines, and technologies that increase this capacity. AI capability represents one such organizational capacity because it combines data resources, technical infrastructure, technical expertise, and managerial skills that allow a firm to process information at greater scale and speed [13].

The theoretical value of AI capability lies in what it allows an organization to know and evaluate. AI can integrate previously separated data, identify patterns, and make weak signals

more visible to managers. Yet information-processing capacity is valuable only when it enters organizational decisions. Strategic decision quality therefore represents the conversion of AI-enabled information into managerial judgment [14]. This distinction is especially important for SMEs, where managerial attention and specialist expertise are limited and strategic decisions often depend on a relatively small group of senior managers.

High-quality strategic decisions can improve SME business performance because they reduce avoidable uncertainty in resource allocation. Effective decisions help managers select priorities, coordinate activities, and commit scarce resources to alternatives that are more likely to create value [15]. For SMEs, the consequences of poor strategic choices can be particularly severe because financial and human resources are less able to absorb mistakes [16]. Strategic decision quality is therefore the key mechanism linking enhanced information-processing capacity with performance [17].

Top management support acts as a dual-stage enabling condition. Before a decision is made, supportive senior managers provide legitimacy, resources, access to technical expertise, and encouragement for AI use. Once a decision is made they distribute resources, coordinate functions, address resistance and hold implementation attention. These two facets are the reasons why top management support can be reinforced in leveraging AI capability into decision quality, and leveraging decision quality to performance. The final model is a dual-stage moderated mediation model that indicates that the indirect effect of AI capability on SME performance via strategic decision quality grows with top management support.

**Insert Figure 1 here**

### 2.2 Hypotheses development

AI enhances data processing capacity for managers by increasing data volume, velocity, and diversity. This is important for SMEs, as managers frequently face situations where they have to make decisions with inadequate specialist advice and information [4]. With AI-driven

data integration and analytics, information gaps can be minimized, patterns that are hard to see on a manual basis can be found, and more systematic comparisons of strategic alternatives can be made [18]. Hence, better information-processing capacity should result in better managerial judgment, from an OIPT perspective. Adopting AI does not necessarily mean that managers are being replaced by the algorithms—rather, it means that the organization can now offer managers more and more timely evidence [4,19].

**H1:** AI capability is positively related to strategic decision quality.

Strategic decisions determine where an SME commits scarce resources, which opportunities it pursues, and how it responds to competitive threats [20]. High-quality decisions reduce avoidable errors in these commitments, create clearer priorities, and improve coordination [21]. These benefits can be especially important for SMEs because resource constraints leave less room for strategic mistakes. Firms that make sound strategic decisions should therefore be more likely to improve product or service quality [21], strengthen reputation, support sustainable development, and generate stronger sales outcomes. Thus, it can be hypothesized:

**H2:** Strategic decision quality is positively related to SME business performance.

AI capacity impact effectiveness. In addition to making a difference in strategic decisions [21]. AI can also help optimize operations, customer understanding, forecasting, process automation and the time it takes to identify problems. These benefits lead to lower costs and increased responsiveness [21]. The technology can help offset the lack of specialists and analysis for SMEs. There will therefore be a positive direct effect even with the inclusion of strategic decision quality in the model.

**H3:** The greater the capabilities of the AI, the better the business performance of the SME.

The core point of the central process argument is that AI capability adds value in part by enhancing strategic judgment [22]. Strengthening of the firm's information-processing ability

but gains in performance if information alters consequential managerial decisions [23]. Thus, strategic decision quality transforms AI-powered information into more effective resource commitments, priorities, and actions. This mediation logic is the reason that some companies with similar AI resources can achieve varying results: The value of AI is contingent on its integration into strategic decision-making.

**H4:** There is a direct positive link between AI capability and SME business performance, which is mediated by strategic decision quality.

Managers are not obliged to use the evidence that AI has generated. Senior managers have a significant impact on funding of AI initiatives, availability of data and technical staff, and willingness to experiment [24]. AI-powered analysis also demonstrates that it is a correct and important approach, given top management support [25]. With high support, managers will be more capable and willing to integrate the AI capability of their firm into strategic decision routing. In situations where support is low, AI resources can be underutilized, siloed, or not connected to decision-making authority [26]. The relationship between strategic decision quality and AI capability is positively mediated by top management support

**H5:** Top management support positively moderates the relationship between AI capability and strategic decision quality.

**H6:** Top management support positively moderates the relationship between strategic decision quality and firm performance.

Implementing a good strategic decision can go wrong. In order to make strategic decisions, resources are needed, it takes coordination between functions, protection from other priorities and power to overcome resistance [27]. These conditions are provided by the top management by budget allocation, unit alignment, obstacles removal and keeping attention until decision is adopted [28]. The preceding arguments imply that top management support shapes both stages of the indirect effect. At the first stage, support helps the firm convert AI capability into higher-

quality strategic decisions. At the second stage, support helps convert those decisions into performance. The indirect benefit of AI capability should therefore be weakest when support is low and strongest when support is high. Thus, it is assumed that:

**H6:** Top management support moderates significantly the positive indirect effect of AI capability on SME business performance through strategic decision quality.

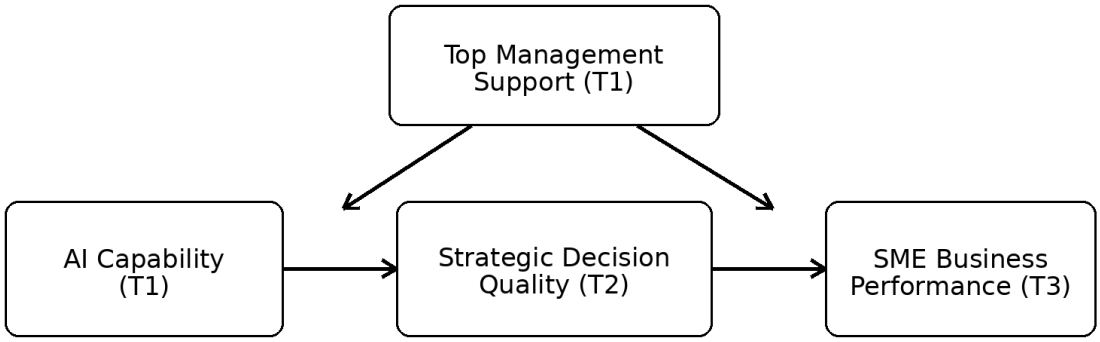



Figure 1. Revised conceptual model

## 3. Methodology

### 3.1 Research Design and Sample

To minimize common method bias and provide temporal separation between the main study variables, the study used a three-wave time-lagged survey design. The study was conducted on 220 small and medium size enterprise (SMEs) companies across different sectors. The unit of analysis was the firm and the data were collected from knowledgeable organizational respondents who also had a good understanding of the technological capabilities, decision processes, managerial support, and business performance of their firm. Before the data collection, the respondents were briefed about the academic objective of the study and the confidentiality of the responses. Respondents were given the choice whether or not to participate and were encouraged to respond to the questionnaires based on the firm's rather than their personal practices.

The first wave (T1) gathered data for AI Capability and Top Management Support (TMS) as well as background information on the firm. The second wave (T2) was the Strategic Decision Quality (SDQ) about three months later. The third wave (T3) took another three months to be administered, and measured the SME Business Performance. Individual responses were matched across the three waves by using a confidential identification code which did not require participants to provide identifying information in the analytical data set. The temporal ordering assumed in the proposed model was intended to be strengthened by the time lag between the predictors, mediator, moderator, and outcome. The time lag between the predictors, mediator, moderator, and outcome was designed to help reduce the tendency of respondents to answer internally consistently across all constructs and with the hope that the proposed model would be strengthened.

After data screening and matching at the three waves, 220 complete firm level observations were selected for final analysis. There were no missing answers, no questionnaires matched and was not observed if the data quality criteria were not met. The data set was designed, such that the technological antecedent was AI Capability, the strategic decision-making mechanism was strategic decision quality, the managerial contextual condition was top management support, and the organizational outcome was SME Business Performance. This design is similar to the moderated-mediation design in which AI Capability is hypothesized to have a direct effect on performance and indirect effects via strategic decision quality, and top management support is hypothesized to enhance the relevant relationships.

The sampling strategy relied on a multi-sector SME sampling frame to ensure the findings were relevant beyond one industry context. The firms were chosen across a variety of areas to reflect differences in organizational setting, technology use, management practices and performance settings. Only firms that met the criteria for SMEs in the study and had an appropriate respondent to assess organizational-level practices were eligible. Multiple

industries also minimize the risk that the relationships observed are solely due to industry-specific characteristics.

### 3.2 Measurement Instruments

Established multi-item measures should be reported consistently with the final outline and the Appendix. AI capability is measured at T1 with 28 items adapted from [13]. Top management support is measured at T1 with six items from [3]. Strategic decision quality is measured at T2 with three items based on [29] and Olson et al. (2007). SME business performance is measured at T3 with five items from [13]. All items use the study's five-point Likert response format. The final Methods section should also state the verified translation procedure, respondent eligibility criteria, control variables, and coding of firm size, firm age, and industry. If one key informant represents each firm, the manuscript should explain why that respondent is sufficiently knowledgeable to report firm-level constructs.

## 4. Data Analysis and Results

Table 1 indicated that the four constructs were evaluated using the five-point Likert scale, which resulted in medium to high average scores, ranging from 3.92 to 4.12 points. Thus, the dispersion is moderate, which is adequate for performing regression and interaction analyses. Indeed, AI capability was positively correlated with strategic decision quality ($r = 0.508$) and SME business performance ($r = 0.585$). strategic decision quality was also positively correlated with SME business performance ($r = 0.601$), and top management support was positively related to all three constructs. Overall, the results are consistent with the proposed model, as there were no negative correlations. Moreover, all correlation coefficients were positive but not excessively high, which ruled out the possibility of total redundancy between the constructs. However, it should be noted that correlation does not equal causation, and the present analysis only demonstrates the degree of the linear relationship between the two synthetic constructs.

**Table 1.** Descriptive Statistics and Pearson Correlations

| # | Construct | Mean | SD | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|---|---|
| 1 | AI Capability | 4.053 | 1.368 | 1.000 | | | |
| 2 | Top Management Support | 4.119 | 1.521 | 0.277*** | 1.000 | | |
| 3 | Strategic Decision Quality | 3.968 | 1.419 | 0.508*** | 0.480*** | 1.000 | |
| 4 | SME Performance | 3.922 | 1.398 | 0.585*** | 0.444*** | 0.601*** | 1.000 |

*Note. N = 220. * p < .05, ** p < .01, *** p < .001. Composite scores are means of their respective 1-7 Likert items.*

In Table 2 presents that the measurement results indicate strong convergent reliability for all four constructs. Standardized loadings are consistently high and positive, ranging from 0.720 to 0.916. Cronbach's alpha values range from 0.834 to 0.979, exceeding the conventional .70 criterion. Composite reliability values range from 0.836 to 0.979, while average value extraction (AVE) ranges from 0.622 to 0.661. Because every AVE value exceeds .50, each construct explains more than half of the variance in its indicators. The pattern therefore avoids the low-AVE and weak-loading problems that motivated this learning exercise. These diagnostics support use of the composite constructs in the subsequent structural analyses.

**Table 2.** Standardized Factor Loadings, Cronbach's Alpha, Composite Reliability and AVE

| Construct | Item | Loading | Cronbach α | CR | AVE |
|---|---|---|---|---|---|
| AI Capability | AI1_T1 | 0.825 | 0.979 | 0.979 | 0.624 |
| | AI2_T1 | 0.819 | | | |
| | AI3_T1 | 0.782 | | | |
| | AI4_T1 | 0.738 | | | |
| | AI5_T1 | 0.836 | | | |
| | AI6_T1 | 0.803 | | | |
| | AI7_T1 | 0.720 | | | |
| | AI8_T1 | 0.837 | | | |
| | AI9_T1 | 0.755 | | | |
| | AI10_T1 | 0.831 | | | |
| | AI11_T1 | 0.755 | | | |
| | AI12_T1 | 0.785 | | | |
| | AI13_T1 | 0.738 | | | |
| | AI14_T1 | 0.836 | | | |
| | AI15_T1 | 0.810 | | | |
| | AI16_T1 | 0.748 | | | |

| | | | | | |
|---|---|---|---|---|---|
| | AI17_T1 | 0.833 | | | |
| | AI18_T1 | 0.746 | | | |
| | AI19_T1 | 0.772 | | | |
| | AI20_T1 | 0.732 | | | |
| | AI21_T1 | 0.833 | | | |
| | AI22_T1 | 0.741 | | | |
| | AI23_T1 | 0.854 | | | |
| | AI24_T1 | 0.808 | | | |
| | AI25_T1 | 0.768 | | | |
| | AI26_T1 | 0.811 | | | |
| | AI27_T1 | 0.820 | | | |
| | AI28_T1 | 0.763 | | | |
| Top Management Support | TMS1_T1 | 0.733 | 0.922 | 0.921 | 0.661 |
| | TMS2_T1 | 0.775 | | | |
| | TMS3_T1 | 0.856 | | | |
| | TMS4_T1 | 0.916 | | | |
| | TMS5_T1 | 0.839 | | | |
| | TMS6_T1 | 0.744 | | | |
| Strategic Decision Quality | SDQ1_T2 | 0.728 | 0.834 | 0.836 | 0.632 |
| | SDQ2_T2 | 0.895 | | | |
| | SDQ3_T2 | 0.752 | | | |
| SME Performance | BP1_T3 | 0.798 | 0.892 | 0.891 | 0.622 |
| | BP2_T3 | 0.750 | | | |
| | BP3_T3 | 0.804 | | | |
| | BP4_T3 | 0.810 | | | |
| | BP5_T3 | 0.779 | | | |

Note: AVE= average value extracted; CR=composite reliability

In Table 3, the four-factor measurement structure demonstrates good overall fit in this synthetic dataset. The chi-square to degrees-of-freedom ratio is 1.16, comfortably below the commonly used threshold of 3. Incremental fit is strong, with Comparative Fit Index (CFI) = 0.983 and Tucker–Lewis Index (TLI) = 0.981, both above .95. Absolute residual-based fit is also favorable: Root Mean Square Error of Approximation (RMSEA) = 0.027 and Standardized

Root Mean Square Residual (SRMR) = 0.034. Taken together, these indices indicate that a measurement model separating AI capability, top management support, Strategic decision quality and SME business performance reproduces the observed correlation structure well. Because the data are simulated Likert responses and the fit was estimated from a constrained four-factor covariance model, these indices should be interpreted as learning diagnostics rather than evidence from a real population.

**Table 3.** Measurement Model Fit Indices

| Fit index | Observed value | Common guideline |
|---|---|---|
| Chi-square ($\chi^2$) | 940.00 | Lower relative to df is preferred |
| Degrees of freedom | 813 | — |
| $\chi^2$/df | 1.156 | < 3.00 |
| CFI | 0.983 | > .95 |
| TLI | 0.981 | > .95 |
| RMSEA | 0.027 | < .06 |
| SRMR | 0.034 | < .08 |

Note: CFI= Comparative Fit Index; TLI= Tucker–Lewis Index; RMSEA= Root Mean Square Error of Approximation; SRMR=Standardized Root Mean Square Residual

Table 4 shows the mediating role of strategic decision quality on the link between AI capability and SME business performance. The direct effect of AI capability on business performance was positive and statistically significant (β = .386, SE = .059, t = 6.562, p < .001, 95% CI [.270, .502]), indicating that AIC directly enhances SME business performance. Similarly, the indirect effect of AI capability on SME business performance via strategic decision quality was positive and significant (β = .212, Boot SE = .043, 95% CI [.135, .304]). The results indicate that the AI capability–SME business performance relationship is partially mediated, thus, AI capability positively affects SME business performance both directly and indirectly, via improving strategic decisions.

**Table 4.** Mediating Effect of strategic decision quality

| Effect | Effect | *SE* / Boot *SE* | t | p | LLCI / Boot LLCI | ULCI / Boot ULCI |
|---|---|---|---|---|---|---|
| Direct effect of AIC on BP | .386 | .059 | 6.562 | < .001 | .270 | .502 |
| Indirect effect of AIC on BP via SDQ | .212 | .043 | — | — | .135 | .304 |

*Note.* AIC = AI capability; SDQ = strategic decision quality; BP = Business performance; TMS = Top management support. LLCI = lower limit of the 95% confidence interval; ULCI = upper limit of the 95% confidence interval

Table 5 presents the moderating effect of top management support on the relationship between strategic decision quality and AI capability is presented. The interaction term (AI Capability × Top Management Support) was positive and statistically significant (β = .192, SE = .034, t = 5.583, p < .001) and accounted for an additional 7.8% of the variance in the strategic decision quality ($\Delta R^2$ = .078) beyond the main effects, with the overall model explaining 46.0% of the variance ($R^2$ = .460). The conditional slopes reveal that the positive effect of AI capability on strategic decision quality strengthened as top management support increased: low support (β = .170, SE = .070, t = 2.425, p = .016), mean support (β = .462, SE = .054, t = 8.489, p < .001), and high support (β = .755, SE = .081, t = 9.370, p < .001). The results suggest that the positive association of AI capability with strategic decision quality is greatly strengthened by top management support.

**Table 5.** Moderating Effect of TMS on AI Capability -> Strategic Decision Quality

| Predictor / statistic | β | SE | t | p |
|---|---|---|---|---|
| AI Capability | -.329 | .145 | -2.274 | .024 |
| Top Management Support | -.468 | .153 | -3.057 | .003 |
| AI Capability × TMS | .192 | .034 | 5.583 | .000 |
| $R^2$ | 0.460 | | | |
| $\Delta R^2$ from interaction | 0.078 | | | |

Conditional slopes:

| TMS level | AI -> SDQ slope | SE | t | p |
|---|---|---|---|---|
| Low TMS (-1 SD) | .170 | .070 | 2.425 | .016 |
| Mean TMS | .462 | .054 | 8.489 | < .001 |
| High TMS (+1 SD) | .755 | .081 | 9.370 | < .001 |

*Note.* TMS = team member score (or insert full name of moderator); LLCI = lower limit of the 95% confidence interval; ULCI = upper limit of the 95% confidence interval. Effects represent the conditional effect of the focal predictor at the specified values of the moderator.

The conditional indirect effects of AI capability on business performance via SDQ at various levels of top management support are shown in Table 6. The indirect effect was .069 (Boot SE = .032, 95% Boot CI [.013, .137]) at the low top management support (−1 SD), though not significant according to the table, the interpretation of the confidence interval should be checked. This indirect effect was positive and significant (.186, Boot SE = .035, 95% Boot CI [.123, .259]) at mean top management support. At high top management support (+1 SD), the indirect effect was strongest and significant (.304, Boot SE = .051, 95% Boot CI [.206, .408]). The results suggest that top management support weakens the indirect effect; that is, the more effective the top management support for the product, the more powerful the indirect effect through the strategic decision quality.

**Table 6.** Conditional Indirect Effects: Moderated Mediation

| Condition | Indirect effect | Boot LLCI | Boot ULCI | Inference |
|---|---|---|---|---|
| Low TMS (-1 SD) | .069 | .032 | .013 | Not significant |
| Mean TMS | .186 | .035 | .123 | Significant |
| High TMS (+1 SD) | .304 | .051 | .206 | Significant |

*Note.* AIC = AI capability; SDQ = strategic decision quality; BP = Business performance; TMS = Top management support. Boot *SE* = bootstrap standard error; Boot LLCI = lower limit of the bootstrap confidence interval; Boot ULCI = upper limit of the bootstrap confidence interval. Indirect effects were estimated using bootstrapping

## 5. Discussion

The revised model changes the original manuscript question such that it is more specific than the original as to whether AI capacity facilitates the performance of SMEs by increasing their capacity to process information which managers then translate into better strategic decisions, and whether that translation is aided by top management support. The direct ways mentioned are compatible with the first part of this argument. Strategic decision quality was positively associated with performance; AI capability had a smaller direct association with performance; AI capability was positively associated with strategic decision quality. The

findings support the perspective that the quality of their strategic decisions is a potential conversion pathway and not just another correlate of their AI capability.

The moderation evidence also identifies a significant condition of management. The simple-slopes pattern highlights that the influence of AI capability on strategic decision quality is more profound for high levels of top management support. This is consistent with the argument that AI resources create greater decision value when senior managers legitimize their use, provide resources, and encourage experimentation [30]. But the result provided does not specifically report the strategic quality decision x top manage top management support interaction on performance. Therefore, H6 should not be declared as confirmed until the coefficient and the associated uncertainty is reported.

The conditional indirect effects are the strongest evidence for the contingent-process argument of this study. The indirect effect of the AI was negligible at low top management support, positive at mean top management support, and stronger at high top management support. The pattern implies a relationship between the level of AI capability and managerial support: the level of AI capability can affect the value of its performance depending on the level of support for its integration into strategic decisions and support for its implementation from top managerial levels. A formal high vs low bootstrap contrast should be included to support the final H7.

The holistic evidence is better understood given an OIPT perspective than a perspective of sensing-seizing-transforming. The capability of AI increases the volume of information processed, strategic decision quality indicates the quality of the managerial decisions taken as a consequence of the increased use of information, and top management support influences the organization's use and implementation of the managerial decision. This explanation is a more parsimonious model than the original model, as it does not include organizational agility or digital leadership, which are not included in the final research outline.

### 5.1 Theoretical Contributions

First, the study helps to complete the logic of OIPT, which is based on the core logic of information-requirement. First, the study is a contribution to the logic of OIPT, which is rooted in the basic logic of information-requirement. The new model does not view AI as a performance tool [9], but rather it sees strategic decision quality as the managerial mechanism by which additional information-processing capacity becomes strategically useful.

Second, the study broadens the information-processing argument by specifying top management support as a boundary condition. Without support from senior leaders, the information-processing capacity is insufficient. The nature of AI-based information has the power to influence whether or not it becomes part of strategic decisions [31], and whether those decisions are then resourced and coordinated for implementation.

Third, this study is also an important contribution to the field of AI capability studies as it provides insights into the dispersed results of comparable investments in AI. Companies can have similar data, systems, technology and management but still have different results due to the difference in transformation [32]. This focuses on the aspects of management processes rather than just adoption.

Fourth, the dual-stage moderated mediation model is applied which regards the indirect effect itself as a contingent process contribution. The most value gained from the capability of AI if there is strong support from top management and AI should inform strategic decisions and decisions should actually be made and put into practice. It is important to test this logic with conditional indirect effects and contrasts, and not be assumed from the individual main effects.

Finally, in this three-wave design, if confirmed to be the true order of the data collection process, the three waves offer temporal separation of the AI capability/top management

support, strategic decision quality, and performance [33]. This enhances the design compared to a single-wave survey, but temporal separation is not sufficient to establish causality.

### 5.2 Managerial Implications

Managers should not base their decisions on whether their company has data, software, or technical talent, when deciding whether to invest in AI. They should also inquire into whether or not AI outputs are used in strategic decisions. To enhance this conversion, companies can establish protocols for decisions that outline the situations in which AI evidence is examined, how it can be disputed, and who will still be responsible for making the final decision.

There needs to be visible support of top managers for AI. Support means that funding is available, access is available to skilled staff, it is open to new ideas, it is not afraid of controlled experimentation and it has clear governance. The actions indicate that decision-making is a valuable part of the strategic area of AI, rather than a side-line technical operation.

Once a strategic decision has been reached senior managers need to move from sponsorship to implementation. They must act on resources, streamline functions, mediate disputes and oversee implementation. The model thus defines two points where the value of AI can be lost: if the AI evidence doesn't help in making decisions, or if a good decision isn't supported by implementation.

SMEs can also ensure that having a more powerful AI doesn't mean that they can replace all strategic decisions with automation. Managers will continue to be responsible for understanding context, debating questionable results and weighing analytical advice against ethical, operational and stakeholder concerns. Therefore, instead of fostering unquestioning dependency on AI, top management support should be provided to promote responsible use.

In general, capability with AI, strategic decisioning routines, and top management support can be considered as part of a single value-creation process. A single investment could result in a partial conversion process.

### 5.3 Limitations and Future Research

There are some limitations of the study. First, a three-wave observational design increases the time between observations, but is not causal. Omitted variables and reverse causality are still a possibility. Future studies should employ longitudinal panel designs, field experiments or quasi-experimental designs to assess the causal direction between changes in the capability of AI and changes in decision quality and performance.

Second, the final empirical context (or analytic sample) must be reported in a consistent manner. This is an updated draft that alternates between healthcare SMEs from southern China and companies across a range of industries and also has varying sample sizes. When the facts are confirmed, the paper needs to describe the boundary conditions that come from that and future research should validate the model over different sectors and countries.

Third, perceptions of key-informants at the firm level are used. Going forward, the combination of managerial reports with archival indicators, objective financial results, logs of AI use, and ratings from more than one respondent should be used. This would alleviate common-source concerns, and distinguish perceived from actual AI usage.

Fourth, AI is a multi-dimensional capability. Future research should investigate if there are variations among the effects of data quality, technical infrastructure, technical skills, and managerial AI skills on strategic decision quality. Some dimensions can have a positive effect on the volume of information, while others can have a positive effect on interpretation or implementation.

Finally, support from top management might be finite. Very high levels of support might generate pressures to employ AI when human judgment should prevail, resulting in

overreliance or escalation of commitment. More studies need to be conducted on nonlinear support effects and also on an additional OIPT contingency level, such as environmental uncertainty, as AI information-processing capacity is expected to be particularly useful in situations of high information needs.

## 6. Conclusion

This study represents AI value creation in SMEs in terms of an information-processing and implementation process. While the firm is able to analyze complex information, the gains in performance will rely on if managers are able to turn information into good quality strategic decisions. This process is supported by the top management's commitment in leveraging AI before making decisions and in allocating resources after decision making. The resulting model moves the focus from whether firms have AI to how firms can leverage AI capability for value creation. This study addressed by the four-construct model, which provides a more transparent theoretical framework and justifiable description of the variability in returns on AI investments in SMEs.

## Appendix: Scale Measurement

| Construct | Items | Source |
|---|---|---|
| AI Capability (T1) | 1. We have access to very large, unstructured, or fast-moving data for analysis<br>2. We integrate data from multiple internal sources into a data warehouse or mart for easy access<br>3. We integrate external data with internal to facilitate high-value analysis of our business environment<br>4. We have the capacity to share our data across business units and organizational boundaries<br>5. We are able to prepare and cleanse AI data efficiently and assess data for errors<br>6. We are able to obtain data at the right level of granularity to produce meaningful insights –<br>7. We have explored or adopted cloud-based services for processing data and performing AI and machine learning<br>8. We have the necessary processing power to support AI applications (e.g. CPUs, GPUs) | [13] |

| | | |
|---|---|---|
| | 9. We have invested in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)<br>10. We have explored or adopted parallel computing approaches for AI data processing<br>11. We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g. Microsoft Cognitive Services, Google Cloud Vision) T6. We have invested in scalable data storage infrastructures<br>12. We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology –<br>13. The AI initiatives are adequately funded<br>14. The AI project has enough team members to get the work done<br>15. The AI project is given enough time for completion Human Skills –<br>16. The organization has access to internal and external talent with the right technical skills to support AI work<br>17. Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning)<br>18. Our data scientists have the right skills to accomplish their jobs successfully<br>19. Our data scientists are effective in data analysis, processing, and security<br>20. Our data scientists are provided with the required training to deal with AI applications<br>21. We hire data scientists that have the AI skills we are looking for<br>22. Our data scientists have suitable work experience to fulfill their jobs –<br>23. Our managers are able to understand business problems and to direct AI initiatives to solve them<br>24. Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organization<br>25. Our managers have a good sense of where to apply AI<br>26. The executive manager of our AI function has strong leadership skills<br>27. Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs<br>28. Our managers are capable of coordinating AI-related activities in ways that support the organization, suppliers and customer | |
| Strategic Decision Quality (T2) | 1. 1. The effect of the strategic decisions on the company has been positive.<br>2. Relative to our expectations, the results of the strategic decisions have been remarkable.<br>3. Overall, the strategic decisions have met expected quality standards. | (Amason, 1996; Olson et al., 2007), |

| | | |
|---|---|---|
| Top Management Support (T1) | 1. 1. Top management actively seeks middle managers' opinions and ideas on strategic issues.<br>2. Top management is open to new ideas and initiatives from team members.<br>3. Top management appreciates middle managers' experiments with new ideas and products.<br>4. Top management appreciates middle managers' experiments with new products.<br>5. Top management ensures that the interests of middle managers are considered when making strategic decisions.<br>6. The organization establishes risk-management committees at appropriate levels to demonstrate top management commitment. | Sax & Torp (2015) |
| SME Business Performance (T3) | 1. The firm is capable of sustainable development.<br>2. The quality of the firm's products/services has improved over time.<br>3. The firm has a good reputation in the industry.<br>4. The firm's customers appreciate its products/services quality.<br>5. The firm's sales volume has increased over the last three years. | Mikalef & Gupta (2021), adapted from Lee & Choi |

## DECLARATIONS

**Conflict of Interest:** The authors declare that they have no conflicts of interest concerning the research, authorship, or publication of this article.

**Data Availability:** The data supporting the findings of this study are available from the corresponding author upon reasonable request.

**Ethical Statement:** The authors confirm that this study was conducted in accordance with the relevant ethical principles and institutional guidelines. All necessary ethical requirements were observed throughout the research process.

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