Journal of Applied Business, Taxation and Economics Research (JABTER)
Vol. 6, No. 1, October 2026 (Page: 141-160) P-ISSN 2828-4976
https://doi.org/10.54408/jabter.v6i1.685 E-ISSN 2808-263X

Does Speed Matter? Business Intelligence, Dynamic Capabilities and Managerial Decision Quality

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Keywords **:** *Business intelligence; Dynamic capabilities; Decision-making speed; Managerial decision quality; PLS-SEM*

Abstract: This study aims to examine the effect of business intelligence (BI) and dynamic capabilities on managerial decision quality, with decision-making speed as a mediating variable, using contingency theory and the dynamic capability view as the theoretical basis. Data were obtained from 157 managers of medium and large manufacturing companies in Banten Province, Indonesia, selected by purposive sampling, and were analyzed using PLS-SEM with SmartPLS 4. The results show that BI (0.390) and dynamic capabilities (0.505) have a positive effect on decision-making speed, while BI (0.250), dynamic capabilities (0.417), and decision-making speed (0.228) have a positive effect on managerial decision quality. In the mediation test, the indirect effect of dynamic capabilities through decision-making speed (0.115) is significant, indicating partial mediation, while the indirect effect of BI (0.089) is not, so BI affects decision quality only through its direct path; the model explains 72.7% of the variance in decision-making speed and 70.6% in decision quality. For manufacturing companies, these results mean that BI contributes to decision quality mainly through the content of its information, and that BI investment has to be accompanied by the development of organizational capabilities.

Introduction

Digital transformation has changed the basis of managerial decision-making in manufacturing companies, where experience and intuition are now complemented by data supplied through business intelligence (BI) systems (Chen et al., 2012). A BI system collects, stores, and analyzes data from various functions of the company and presents the results as information for managers (Popovič et al., 2012; Trieu, 2017). In Indonesia, the Making Indonesia 4.0 roadmap places the digitalization of manufacturing among the national priorities (Ministry of Industry, 2018), and since manufacturing is the largest contributor to the national gross domestic product (Statistics Indonesia, 2024), the quality of managerial decisions in this sector has consequences beyond individual companies.

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P-ISSN 2828-4976
E-ISSN 2808-263X

The adoption of a BI system, however, does not automatically produce benefits for the organization. Trieu (2017) describes BI value as something created indirectly, only after information has been turned into managerial action. Božič and Dimovski (2019) found that BI created value only in organizations with sufficient absorptive capacity to assimilate and exploit the information, and Chen and Lin (2021) reported that the effect of BI capabilities on performance ran through specific organizational mechanisms rather than directly; the relevant question is therefore how, rather than whether, BI improves managerial decisions. Decision-making speed is one candidate mechanism, given that Eisenhardt (1989) identified decision speed as a source of competitive advantage in high-velocity environments, Baum and Wally (2003) found that strategic decision speed is associated with growth and profitability, and Alzghoul et al. (2024) showed that BI capabilities improve firm performance through both the speed and the comprehensiveness of decision-making.

Banten Province was chosen as the research setting because the processing industry accounts for the largest share of its economy (Statistics Indonesia – Banten Province, 2024) and because its manufacturing base is diverse: steel and petrochemical plants are concentrated in Cilegon, food, pharmaceutical, and animal feed producers in Cikande (Serang Regency), and consumer goods, cosmetics, and automotive component manufacturers in the Tangerang corridor. Companies in these areas operate under fluctuating commodity prices, competition from imported products, and frequent regulatory changes. Eisenhardt (1989) and Shepherd and Rudd (2014) would call this a dynamic environment, where how fast and how well managers decide both affect a firm's competitiveness.

Three gaps motivate the study. The first concerns the outcome variable. Most BI research measures firm performance (Chen & Lin, 2021; Torres et al., 2018), while the quality of managerial decisions, which BI touches much more directly, is seldom measured (Wieder & Ossimitz, 2015; Li et al., 2022). Indonesian research is no exception; Nasution and Jeefry (2026) examined the effect of an ERP-based management information system on employee productivity, but not on decision quality. The second gap concerns mechanisms. Few studies have asked what connects technological and organizational capabilities to decision quality, and those that test decision speed as a mediator were mostly conducted outside developing countries (Alzghoul et al., 2024; Cheng et al., 2020). The third gap is theoretical. Studies tend to rely on either an information technology perspective or a strategy perspective, whereas the problem involves both; for this reason we combine contingency theory with the dynamic capability view (Otley, 2016; Teece, 2007).

Our aim is to examine the relationship of business intelligence and dynamic capabilities with managerial decision quality, and to test whether decision-making speed links them.

This study contributes in three ways. First, it uses managerial decision quality, rather than firm performance, as the dependent variable, so that the model captures the outcome closest to the actual use of BI; second, it tests decision-making speed as the link between BI, dynamic capabilities, and decision quality, which has rarely been done (Alzghoul et al., 2024; Trieu, 2017); and third, it combines contingency theory and the dynamic capability view (Otley, 2016; Teece, 2007) in one model tested with data from Indonesian manufacturing companies. In practical terms, the results can help managers identify what, besides the technology itself, needs to be in place so that BI investment leads to better decisions and not only faster ones.

This article is structured as follows: Section 2 describes the literature review and hypothesis development, Section 3 describes the research method, including the research

design, population and sample, operationalization of variables, and data analysis techniques; Section 4 presents the results and discussion; and Section 5 sets out the conclusions, implications, and limitations.

Contingency theory and dynamic capability view

Contingency theory starts from the idea that there is no single best design for control and information systems; a system is effective when it fits the organization's environment, technology, and strategy (Donaldson, 2001; Otley, 2016). Within this framework, a BI system is treated as one configuration of the management information system whose value depends on the fit between the information it provides and the decisions managers face, and in dynamic industries such decisions require information that is fast, integrated, and forward-looking. Ekasari et al. (2026) illustrate the same fit logic in the Indonesian context: in their design of an accounting information system for a digital startup, the technical components had to be aligned with the work routines and interactions of the users.

The second theoretical perspective, the dynamic capability view (DCV), was introduced by Teece et al. (1997) to explain how firms integrate, build, and reconfigure internal and external competencies when their environment changes rapidly. Teece (2007) subsequently categorized dynamic capabilities into three clusters: sensing (detecting opportunities and threats), seizing (mobilizing resources to seize opportunities), and reconfiguring (rearranging assets and organizational structure). Eisenhardt and Martin (2000) added that in volatile markets, dynamic capabilities are manifested through simple and rapid organizational processes, including strategic decision-making. Together, these two perspectives underpin the logic of the research model: contingency theory explains why BI needs to be aligned with the decision context, while DCV explains why organizational capabilities are needed to effectively convert information into rapid and appropriate actions, in line with Torres et al. (2018) who position BI as an enabler of organizational dynamic capabilities.

Business intelligence

Business intelligence refers to the techniques, technologies, systems, and applications used to analyze business data so that an organization understands its own situation and can decide on time (Chen et al., 2012). Popovič et al. (2012) describe BI maturity in terms of two dimensions, namely information quality and the use of information in analytical decision-making. In a systematic review, Trieu (2017) stresses that BI creates value through a chain: good systems and good information first have to be used effectively before they have any organizational impact. Kulkarni et al. (2017) add that BI capability is closely linked to how strongly an organization is oriented toward analytical decision-making. Building on this work, BI is measured here with three reflective indicators adapted from Popovič et al. (2012) and Trieu (2017): information quality and relevance, accessibility and speed of information presentation, and data integration and analytical capability.

Dynamic capabilities

Dynamic capabilities in this study are operationalized, following Teece (2007), into three dimensions: sensing, seizing, and reconfiguring. In the manufacturing context, sensing is evident in monitoring market trends, technology, and regulations; seizing is evident in the speed of resource allocation to seize opportunities; and reconfiguring is evident in periodically adjusting strategies, business processes, and organizational structures (Teece et al., 1997;

P-ISSN 2828-4976
E-ISSN 2808-263X

Teece, 2007). Awan et al. (2021) show why these capabilities matter for data analytics: in their sample, big data analytics capability improved decision quality in firms that had embedded data-driven insight in their managerial routines.

Decision-making speed

Decision-making speed refers to how quickly an organization completes the strategic decision process, from problem identification to commitment to action (Baum & Wally, 2003). Eisenhardt (1989) reported a counter-intuitive result: fast decision-makers actually utilize more real-time information, not less, than slow decision-makers. Shepherd and Rudd (2014), in their review of the strategic decision-making literature, list the organization's internal context, including the support provided by its information systems, among the factors that affect decision speed. Referring to this argument, this study measures decision-making speed through three indicators: speed of response to urgent situations, efficiency of the decision process in the face of bureaucratic obstacles, and timeliness of decisions without sacrificing maturity of judgment (Baum & Wally, 2003; Eisenhardt, 1989).

Quality of managerial decisions

Managerial decision quality describes the extent to which a decision effectively achieves its objectives, relies on adequate information and analysis, and is consistent with the organization's strategic direction (Dean & Sharfman, 1996). Dean and Sharfman (1996) themselves demonstrated that a rational-procedural decision process results in higher effectiveness, indicating that process quality contributes to outcome quality. In the analytics era, Li et al. (2022) demonstrated that the use of big data analytics boosts organizational decision quality by improving the quality of the information on which it is based. Following these arguments, managerial decision quality is measured with three indicators: whether decisions are accurate and based on evidence, whether alternatives and risks are considered thoroughly, and whether the outcomes are effective and consistent with strategy (Dean & Sharfman, 1996).

The relationship between business intelligence and decision-making speed

BI integrates data from different functions and makes them available for analysis in near real time, so that managers spend less time collecting, processing, and interpreting information (Popovič et al., 2012); Eisenhardt (1989) similarly found that fast decision-makers in high-velocity environments relied on real-time information without sacrificing analytical depth. Empirical studies support this argument: Cheng et al. (2020) found that BI accelerates the internationalization of firms through organizational agility, and Alzghoul et al. (2024) showed directly that BI capabilities increase decision-making speed. Accordingly, the first hypothesis is proposed:

H1. Business intelligence has a positive effect on decision-making speed.

The relationship between dynamic capabilities and decision-making speed

Organizations with strong sensing capabilities are able to detect change signals earlier, thus having longer decision lead times; seizing capabilities enable the mobilization of resources without delay; while reconfiguring capabilities keep the organizational structure lean so that decision paths are not convoluted (Teece, 2007). Eisenhardt and Martin (2000) added that in dynamic environments, dynamic capabilities manifest as simple, rapid, and

knowledge-based decision processes that are situationally generated. Accordingly, the second hypothesis is proposed:
H2. Dynamic capabilities have a positive effect on decision-making speed.

The relationship between decision-making speed and the quality of managerial decisions

Baum and Wally (2003) demonstrated that the speed of strategic decisions boosts firm performance, while Eisenhardt (1989) showed that rapid decisions in turbulent environments do not necessarily sacrifice quality; rapid decision-makers even tend to develop more alternatives simultaneously. Timely decisions allow organizations to act while the window of opportunity is still open and information is not outdated, thus increasing decision effectiveness (Shepherd & Rudd, 2014). Accordingly, the third hypothesis is proposed:
H3. Decision-making speed has a positive effect on the quality of managerial decisions.

The relationship between business intelligence and the quality of managerial decisions

In addition to the indirect route of speed, business intelligence is also believed to directly improve the quality of managerial decisions by enriching the substance of the information underlying the decisions themselves. Within the information processing view, the effectiveness of organizational decisions depends on the match between information needs and existing information processing capabilities; business analytics strengthens these processing capabilities, which in turn helps boost decision-making effectiveness (Cao et al., 2015; Cao et al., 2019). BI systems also provide a more accurate, relevant, and comprehensive fact base, thereby reducing uncertainty and ambiguity in the decision-making process (Popovič et al., 2012).

Empirical evidence supports this direct path argument. Visinescu et al. (2017) found that information quality and BI system usage improve perceived decision quality, especially for complex problems. Ghasemaghaei et al. (2018) even demonstrated that all dimensions of data analytics competency, from data quality, analytical skills, domain knowledge, to tool sophistication, significantly boost decision quality. Li et al. (2022) reported similar results regarding the use of big data analytics, as did Wieder and Ossimitz (2015), who modeled the direct and indirect effects of BI management quality on managerial decision-making quality. Accordingly, the fourth hypothesis is proposed:
H4. Business intelligence has a positive effect on the quality of managerial decisions.

The relationship between dynamic capabilities and the quality of managerial decisions

Dynamic capabilities are essentially higher-level decision-making capabilities. Teece (2007) explicitly positions decision rules as a manifestation of dynamic capabilities, while Eisenhardt and Martin (2000) state that strategic decision-making itself is a manifestation of dynamic capabilities. The mechanisms of their direct influence can be explained by dimension: strong sensing enables managers to more accurately detect signals of opportunities and threats, so that decisions are based on a more precise understanding of the situation (Helfat & Peteraf, 2015); seizing ensures resources are mobilized to the right choice at the right time; and reconfiguring keeps decisions relevant and adaptive to change. Through the concept of dynamic managerial capabilities, Adner and Helfat (2003) assert that differences in the quality of managerial decisions between companies are rooted in differences in the managerial capabilities that underpin their decision-making processes.

Empirically, Shamim et al. (2019), using the dynamic capabilities view, found that decision-making capabilities derived from data resource management significantly influence

P-ISSN 2828-4976
E-ISSN 2808-263X

decision quality. Torres et al. (2018) demonstrated how sensing-seizing-transforming capabilities contribute to performance through business process improvements. However, direct examination of the relationship between dynamic capabilities and managerial decision quality is still relatively rare, making this pathway an original contribution of the research. Accordingly, the fifth hypothesis is proposed:
H5. Dynamic capabilities have a positive effect on the quality of managerial decisions.

The mediating role of decision-making speed

The mediation argument builds on the BI value chain (Trieu, 2017). Technological and organizational capabilities may improve decision quality directly, but they may also do so by changing the decision process. In the case of BI, integrated data that are close to real time cut the time needed to spot problems and weigh alternatives. Eisenhardt (1989) observed that fast decision-makers use more real-time information, and Alzghoul et al. (2024) reported that BI capability raises firm performance partly through decision speed. In the case of dynamic capabilities, sensing gives managers earlier warning, seizing removes delays in committing resources, and reconfiguring shortens decision paths (Teece, 2007). Decisions are then taken while the information is still current and the opportunity is still open (Shepherd & Rudd, 2014). If speed is indeed one of the routes, part of the effect of both capabilities on decision quality should pass through it. Using the typology of Zhao et al. (2010), the study also checks whether any mediation is indirect-only or complementary. Two mediation hypotheses follow:
H6a. Decision-making speed mediates the relationship between business intelligence and managerial decision quality.
H6b. Decision-making speed mediates the relationship between dynamic capabilities and managerial decision quality.

Research methods

Research design

This study used a quantitative approach with an explanatory survey design in order to test the causal relationships among the latent variables of the proposed model, and the data were collected cross-sectionally through a structured questionnaire delivered to respondents at their company locations. The unit of analysis is the manufacturing company; managers acted as key informants, assessing the condition of their own organizations with respect to business intelligence, dynamic capabilities, decision-making speed, and decision quality.

Population, sample, and sampling techniques

The population consists of medium and large manufacturing companies in Banten Province, of which 58 were identified in Cilegon City, Serang Regency and City, Tangerang Regency and City, Lebak Regency, and Pandeglang Regency, covering the steel, petrochemical, chemical, food and beverage, pharmaceutical, consumer goods, automotive component, and building material sectors. Respondents were selected by purposive sampling with three criteria, namely (1) holding a position from supervisor to director, (2) having held that position for at least one year, and (3) being involved in tactical or strategic decision-making in their unit; a company could be represented by more than one respondent as long as the respondents came from different functions.

The sample size followed from these criteria, since all respondents who met them and returned a complete questionnaire were included in the analysis (Etikan et al., 2016); for this purpose, 305 questionnaires were distributed.

Operationalization of variables and instruments

All constructs were measured reflectively using a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree), through 22 statements adapted from validated instruments in previous studies and translated into Indonesian through a back-translation procedure.

Table 1. Operationalization of Research Variables

Variables	Indicator	Item code	Amount	Adaptation sources
Business Intelligence (X1)	Quality & relevance of information	bi1, bi5	6	Popovič et al. (2012); Trieu (2017)
	Accessibility & speed of information	bi2, bi4		
	Data integration & analytics capabilities	bi3, bi6		
Dynamic Capability (X2)	Sensing	kd1, kd2	6	Teece et al. (1997); Teece (2007)
	Seizing	kd3, kd4		
	Reconfiguring	kd5, kd6		
Decision Making Speed (Z)	Response speed	kk1, kk2	5	Baum & Wally (2003); Eisenhardt (1989)
	Efficiency of the decision process	kk3, kk4		
	Punctuality without sacrificing quality	kk5		
Managerial Decision Quality (Y)	Accuracy & data-driven	km1, km2	5	Dean & Sharfman (1996)
	Completeness of consideration	km3		
	Strategic effectiveness & consistency	km4, km5		

In this study, business intelligence is measured by six indicators adapted from Popovič et al. (2012) and Trieu (2017): accuracy and reliability of system-generated information (bi1), ease of access to information for those who need it (bi2), integration of data from various organizational functions (bi3), speed of report presentation and analysis (bi4), relevance of information to decision-making needs (bi5), and analytical support for future planning (bi6).

The dynamic capability construct is measured by six indicators adapted from Teece et al. (1997) and Teece (2007): regular monitoring of changes in the business environment (kd1), early detection of opportunities and threats (kd2), agility in allocating resources to capture

P-ISSN 2828-4976
E-ISSN 2808-263X

opportunities (kd3), effective decision follow-up mechanisms (kd4), periodic review of business strategies and processes (kd5), and the ability to adjust work methods and organizational structures (kd6).

The decision-making speed construct uses five indicators adapted from Baum and Wally (2003) and Eisenhardt (1989): completion of important decision processes within a reasonable time (kk1), speed of response to urgent situations (kk2), smoothness of the decision process from bureaucratic obstacles (kk3), information system support for accelerating analysis (kk4), and balance between speed and maturity of consideration (kk5).

Managerial decision quality is measured with five items adapted from Dean and Sharfman (1996): achievement of decision objectives (km1), the use of adequate data and analysis as the basis for decisions (km2), completeness in considering alternatives and risks (km3), consistency of decisions with long-term strategy (km4), and the overall effectiveness of decision results (km5). The four constructs and their 22 items (bi1–bi6, kd1–kd6, kk1–kk5, and km1–km5) are summarized in Table 1.

Controlling common method bias

Common method bias was a concern because each respondent answered all items at the same sitting (Podsakoff et al., 2003). Two types of remedies were applied: procedurally, items from different constructs were randomized and presented without variable labels, respondents remained anonymous, and statements were worded in plain language; statistically, the full collinearity VIF approach was used, with values below 3.3 taken as an indication that the model is free from common method bias (Kock, 2015).

Data analysis techniques

The data were analyzed with partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4 (Ringle et al., 2024). PLS-SEM was chosen for three reasons. The study aims to explain and predict a target construct, the model contains mediating paths, and PLS-SEM works well with moderate samples without requiring multivariate normality (Hair et al., 2019; Hair et al., 2022).

Evaluation of the measurement model (outer model) includes: (1) indicator reliability with an expected outer loading of at least 0.708; (2) internal consistency reliability with composite reliability and Cronbach's alpha in the range of 0.70–0.95; (3) convergent validity with an average variance extracted (AVE) of at least 0.50; and (4) discriminant validity using the heterotrait–monotrait ratio (HTMT) criterion with a conservative threshold of 0.85 (Hair et al., 2019; Henseler et al., 2015).

The evaluation of the structural model (inner model) includes: (1) checking for collinearity between exogenous constructs with a VIF preferably below 3 and in no case above 5; (2) the coefficient of determination R-squared for endogenous constructs; (3) the effect size f-squared to assess the relative contribution of each predictor; (4) predictive relevance through the PLSpredict procedure; and (5) the significance of the path coefficients was tested by bootstrapping 5,000 subsamples using a one-tailed test at a significance level of 5% according to the direction of the hypothesis (Hair et al., 2019; Hair et al., 2022).

Mediation testing followed the procedures of Nitzl et al. (2016) and the typology of Zhao et al. (2010): the significance of the indirect effect was tested through bootstrapping; if the indirect effect was significant while the direct effect was insignificant, the mediation was classified as indirect-only (full mediation); if both were significant in the same direction, the

mediation was classified as complementary (partial mediation). The magnitude of mediation was reported using variance accounted for (VAF) as supplementary information.

Results and discussion

Respondent profile

Data were collected through a questionnaire distributed to managers of medium- and large-scale manufacturing companies in Banten Province, selected purposively on the criterion that they were involved in decision-making processes within their companies. Of the 305 questionnaires distributed, 244 were returned, yielding a response rate of 80.0%. Of these, 87 were unusable because they had been incompletely filled in or because the respondents did not meet the specified criteria. A total of 157 questionnaires (51.5% of those distributed) were therefore processed and analyzed.

Male respondents predominated (102; 65.0%), with 55 women (35.0%). All respondents were university graduates: 93 (59.2%) held a bachelor's degree and 64 (40.8%) a master's degree, indicating sufficient capacity to interpret the statements on business intelligence and dynamic capabilities.

By position, the sample comprised 86 supervisors (54.8%), 68 managers (43.3%), and 3 senior managers (1.9%). In terms of tenure, 83 respondents (52.9%) had worked for more than 10 years, 56 (35.7%) for 5 to 10 years, and 18 (11.5%) for less than 5 years; 139 respondents (88.5%) had thus served for at least five years and were familiar with information management practices and decision-making processes in their companies.

Regarding involvement in strategic decision-making, 104 respondents (66.2%) reported being frequently involved and 53 (33.8%) always involved, so that all respondents were active participants in their companies' decision-making processes. As for the implementation of data-based information systems, 150 respondents (95.5%) reported that their company had implemented such a system fully and 7 (4.5%) partially. These characteristics indicate that respondents came from companies with adequate information infrastructure, so that their assessments of business intelligence rest on actual experience of use.

Descriptive statistics

The 157 usable questionnaires had no missing answers, and every response was within the 1–5 range. Variable means were between 3.84 and 4.30, all above the midpoint. So managers rated BI, dynamic capabilities, decision speed, and decision quality in their firms as fairly good.

BI has a mean of 3.84 and the largest standard deviation (0.99). Most firms use BI, but at different levels of maturity: some have integrated their information well, others are still at a basic stage. The item with the lowest mean is, interestingly, the relevance of information for decision needs (BI5 = 3.61). The weak spot is therefore not the technology itself but whether its output answers the questions managers actually have.

The means for dynamic capabilities (3.94; standard deviation 0.96) and decision-making speed (3.93; standard deviation 0.92) differ by only 0.01. Manufacturing firms in Banten appear to be used to watching their business environment, taking up opportunities, and adjusting, and they are also able to finish decision processes within a reasonable time. That the two scores are so close is in line with the model: firms that are used to anticipating change also tend to decide more quickly.

P-ISSN 2828-4976
E-ISSN 2808-263X

Managerial decision quality has the highest mean (4.30) and the smallest spread (standard deviation 0.81). Managers thus judge their firms' decisions as reaching their goals, based on data, and consistent with long-term strategy. This should be read carefully, because managers are rating the quality of their own decisions, and such self-ratings tend to be optimistic. The fact that decision quality is rated higher than the capabilities that support it also shows why the research question matters: how far is decision quality really shaped by business intelligence and dynamic capabilities, and through which mechanisms?

Evaluation of the measurement model

The measurement model was assessed through indicator reliability, internal consistency reliability, and convergent validity (Hair et al., 2022). The results are shown in Table 2.

Table 2. Outer loading, reliability, and convergent validity

Construct	Indicator	Outer Loading	Cronbach's Alpha	CR (rho_c)	AVE
Business Intelligence	BI1	0.777	0.881	0.910	0.629
	BI2	0.781			
	BI3	0.853			
	BI4	0.804			
	BI5	0.828			
	BI6	0.709			
Dynamic Capabilities	KD1	0.777	0.872	0.904	0.611
	KD2	0.722			
	KD3	0.768			
	KD4	0.852			
	KD5	0.799			
	KD6	0.767			
Decision Making Speed	KK1	0.722	0.813	0.870	0.575
	KK2	0.805			
	KK3	0.825			
	KK4	0.764			
	KK5	0.664			
Quality of Managerial Decisions	KM1	0.757	0.848	0.891	0.622
	KM2	0.793			
	KM3	0.796			
	KM4	0.821			
	KM5	0.774			

Indicator loading tests aim to determine the strength of the correlation between indicator scores and construct scores. An indicator is considered valid if its loading value is above 0.70, although loadings above 0.60 may still be acceptable where convergent validity is otherwise established (Hair et al., 2022). As shown in Table 2, the outer loadings range from 0.664 (KK5) to 0.853 (BI3), and all 22 indicators were retained; with composite reliability between 0.870 and 0.910 and Cronbach's alpha between 0.813 and 0.881, every construct exceeds the 0.70 reliability threshold. The average variance extracted (AVE) values, which

range from 0.575 to 0.629, also fall above the recommended cut-off of 0.50, thus meeting convergent validity.

Discriminant validity

Discriminant validity was examined using three criteria: cross-loading, the Fornell-Larcker criterion, and the heterotrait-monotrait ratio (HTMT). Table 3 presents the cross-loadings of all indicators.

Table 3. Cross-loadings of indicators

Indicator	BI	KD	KK	KM
BI1	0.777	0.627	0.614	0.648
BI2	0.781	0.618	0.646	0.651
BI3	0.853	0.684	0.636	0.609
BI4	0.804	0.670	0.657	0.648
BI5	0.828	0.657	0.653	0.596
BI6	0.709	0.604	0.598	0.505
KD1	0.747	0.777	0.707	0.638
KD2	0.556	0.722	0.625	0.597
KD3	0.560	0.768	0.580	0.567
KD4	0.696	0.852	0.633	0.683
KD5	0.655	0.799	0.632	0.671
KD6	0.574	0.767	0.668	0.623
KK1	0.600	0.663	0.722	0.589
KK2	0.592	0.624	0.805	0.561
KK3	0.621	0.620	0.825	0.597
KK4	0.660	0.604	0.764	0.593
KK5	0.550	0.596	0.664	0.576
KM1	0.551	0.613	0.648	0.757
KM2	0.691	0.699	0.606	0.793
KM3	0.641	0.610	0.622	0.796
KM4	0.595	0.614	0.583	0.821
KM5	0.552	0.640	0.580	0.774

Based on Table 3, each indicator loads the highest on its own construct compared to other constructs, applicable to all 22 indicators without exception. The cross-loading criterion thus indicates that discriminant validity is met.

Table 4. Fornell-Larcker Criterion (diagonal = square root of AVE)

Construct	BI	KD	KK	KM
Business Intelligence (BI)	0.793			
Dynamic Capabilities (KD)	0.811	0.782		
Decision Speed (KK)	0.800	0.822	0.758	
Decision Quality (KM)	0.771	0.808	0.771	0.788

P-ISSN 2828-4976
E-ISSN 2808-263X

Table 5. Heterotrait-monotrait ratio (HTMT)

Construct Pair	HTMT
Dynamic Capabilities <-> Business Intelligence	0.922
Decision Speed <-> Business Intelligence	0.945
Decision Speed <-> Dynamic Capabilities	0.975
Decision Quality <-> Business Intelligence	0.887
Decision Quality <-> Dynamic Capabilities	0.936
Decision Quality <-> Decision Speed	0.929

Meanwhile, the Fornell-Larcker criterion (Table 4) indicates that the square root of the AVE of several constructs is slightly below their inter-construct correlations, and the HTMT values for all pairs of constructs (Table 5) exceed the conservative threshold of 0.85 (Henseler et al., 2015). These findings should be read in the theoretical context of the model: business intelligence, dynamic capabilities, decision-making speed, and managerial decision quality are conceptually closely related capability-to-results chains, so high inter-construct correlations are more likely a theoretically explicable consequence, rather than a measurement artifact. Nevertheless, the high HTMT values are still recognized as an indication of empirical overlap between constructs, which should be noted as a limitation of the study; future research is recommended to sharpen the differentiation of measurement items between constructs and use data collection designs that separate the sources or timing of measurement to reduce the potential for common method bias (Podsakoff et al., 2003).

Evaluation of the structural model

Figure 2 presents the results of the research model estimation from SmartPLS 4, complete with outer loadings of all indicators, path coefficients between constructs, and determination coefficients of endogenous constructs.

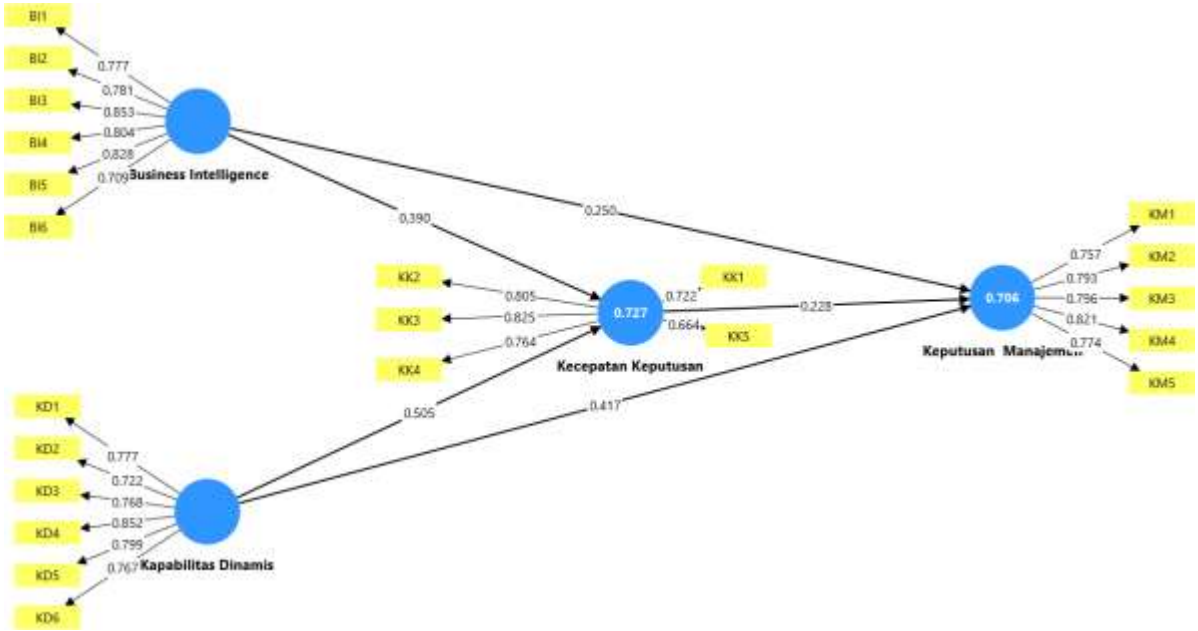


Figure 2. Research model estimation results (SmartPLS 4 output)

As seen in Figure 2, all indicators load on their respective constructs with loadings ranging from 0.664 to 0.853. Looking at the indicator with the highest loading in each construct tells us more about what each variable means in practice. In business intelligence, the strongest indicator is cross-functional data integration (BI3 = 0.853); in other words, for

Banten manufacturing managers, the essence of BI is not in the sophistication of its display, but in its ability to combine data from various parts of the organization into a single, complete picture. For dynamic capabilities, the strongest indicator is an effective mechanism for following up decisions (KD4 = 0.852), which belongs to the seizing dimension. A firm's ability to adapt, then, depends more on carrying decisions through than on simply noticing change.

In terms of decision-making speed, the strongest indicator is the smoothness of the process from bureaucratic obstacles (KK3 = 0.825), which means that decision speed is essentially a matter of organizational process design, namely reducing convoluted approval chains, not simply a matter of individual haste. Correspondingly, the indicator of balance between speed and maturity of judgment (KK5 = 0.664) is the weakest reflection of this construct, indicating that respondents interpret speed more as a smooth process than as a compromise of caution. As for the quality of managerial decisions, the strongest indicator is the consistency of decisions with long-term strategy (KM4 = 0.821); the quality of decisions in the field is apparently interpreted not only as the accuracy of the momentary results, but also the alignment of each decision with the company's strategic direction.

Decision-making speed is predicted by business intelligence (0.390) and dynamic capabilities (0.505). Managerial decision quality is predicted by decision-making speed (0.228), business intelligence (0.250), and dynamic capabilities (0.417). This pattern shows that organizational capabilities are consistently the strongest drivers of both outcome constructs. The coefficients of determination for both endogenous constructs indicate considerable explanatory power of the model: 72.7% of the variation in decision-making speed and 70.6% of the variation in managerial decision quality are explained by the model, leaving less than a third of the variation attributable to factors outside the model.

Before hypothesis testing, collinearity between constructs was first examined using variance inflation factor (VIF) values. The highest VIF was 3.9, below the threshold of 5, thus no collinearity issues were found (Hair et al., 2022). The model's SRMR value was 0.081, slightly above the conservative threshold of 0.08, and was noted as a limitation of the model. Meanwhile, the R-square for decision-making speed was 0.727 and managerial decision quality was 0.706, both of which are considered strong and confirm the model's considerable explanatory power.

Hypothesis testing was conducted using a bootstrapping procedure with 5,000 subsamples (one-tailed, 5% alpha). Table 6 presents the results of the direct path hypothesis test.

Table 6. Results of direct path hypothesis testing

Hypothesis	Path	Coefficient	t-statistic	p-value	Decision
H1	BI -> Decision Speed	0.390	5.772	< 0.001	Accepted
H2	Dynamic Capabilities -> Decision Speed	0.505	6.926	< 0.001	Accepted
H3	Decision Speed -> Decision Quality	0.228	1.784	0.037	Accepted
H4	BI -> Decision Quality	0.250	2.109	0.018	Accepted
H5	Dynamic Capabilities -> Decision Quality	0.417	4.311	< 0.001	Accepted

P-ISSN 2828-4976
E-ISSN 2808-263X

Table 6 shows that business intelligence has a significant effect on decision-making speed (coefficient 0.390; significant at the 0.001 level), so H1 is accepted. Dynamic capabilities also have an effect on decision-making speed with a coefficient of 0.505 (significant at the 0.001 level), so H2 is accepted. Decision-making speed is proven to have an effect on managerial decision quality with a coefficient of 0.228 (significant at the 0.05 level), which confirms H3. Business intelligence also has a direct effect on managerial decision quality with a coefficient of 0.250 (significant at the 0.05 level), so H4 is accepted, while dynamic capabilities show a greater effect on managerial decision quality with a coefficient of 0.417 (significant at the 0.001 level), confirming H5. Since all t-statistic values on the direct paths are above 1.645, it can be concluded that the five direct path hypotheses are supported by the data.

Mediation testing

Mediation testing was conducted by examining the significance of specific indirect effects from bootstrapping results, following the procedure of Nitzl et al. (2016), and the type of mediation was classified according to Zhao et al. (2010). The results are presented in Table 7.

Table 7. Results of mediation testing (specific indirect effects)

Hypothesis	Indirect Path	Coefficient	t-statistic	p-value	Decision
H6a	BI -> Decision Speed -> Decision Quality	0.089	1.600	0.055	Rejected
H6b	Dynamic Capabilities -> Decision Speed -> Decision Quality	0.115	1.717	0.043	Accepted

The test results show that the indirect effect of business intelligence on managerial decision quality through decision-making speed is not significant (coefficient 0.089; p = 0.055), so H6a is rejected. Referring to the typology of Zhao et al. (2010), this pattern is classified as direct-only (no mediation) because the direct effect remains significant. This is different for dynamic capabilities: the indirect effect is 0.115 and is significant at the 0.05 level, so H6b is accepted. Both the direct and the indirect effect are significant and positive, so decision-making speed partially mediates the effect of dynamic capabilities on decision quality; in the terms of Zhao et al. (2010), this is complementary mediation.

Discussion

Decision-making speed turns out to depend on technological as well as organizational capabilities. BI increases speed (H1), as also reported by Alzghoul et al. (2024) and Trieu (2017); integrated systems simply reduce the time needed to find, process, and present information. Dynamic capabilities, however, have a larger effect (H2; 0.505 against 0.390). The indicator results suggest why. Speed is reflected most strongly by how smoothly a decision moves past bureaucratic obstacles (KK3), not by how fast information arrives. In medium and large manufacturing companies, many of which belong to national or multinational groups with several approval layers, the duration of a decision is often determined by the number of approvals it requires rather than by the speed at which data become available; the follow-up mechanisms in the seizing dimension (KD4 = 0.852) act on this bottleneck (Eisenhardt & Martin, 2000; Teece, 2007). This supports the contingency

argument that technology yields the greatest benefit in organizations that are prepared to use it (Otley, 2016).

Decision-making speed has a positive effect on decision quality (H3), in line with Baum and Wally (2003) and Eisenhardt (1989), but the coefficient (0.228; t = 1.784) is the smallest in the model, so speed contributes to decision quality without being its main driver. Two explanations can be offered. The first is that the speed–quality relationship depends on context, as shown by Forbes (2005), whose fast-deciding new ventures were more likely to close, and by Shepherd et al. (2021), who found that the effect of speed on decision quality varies with conditions in the business environment; the second is that many decisions in capital-intensive manufacturing, such as adding capacity, signing long-term supply contracts, or changing a production line, are difficult to reverse, so careful deliberation may matter as much as timeliness. The lowest loading in the speed construct belongs to KK5 (0.664), the item on balancing speed with maturity of judgment, which is consistent with this explanation and suggests that respondents distinguish speed from caution.

BI also has a direct effect on decision quality (H4; 0.250), which agrees with Visinescu et al. (2017), Ghasemaghaei et al. (2018), and Cao et al. (2015), who attribute the benefit of analytics to accurate, relevant, and integrated information, whereas the indirect path through speed is not significant (H6a; 0.089, p = 0.055). This result differs from Alzghoul et al. (2024), in whose study speed carried part of the effect of BI capability, and two explanations are possible: their dependent variable was firm performance, while decision quality depends more on the content of information than on how quickly it is delivered; and 95.5% of the respondents in this study work in companies that have fully implemented data-based information systems, so fast access to data has probably become standard and no longer distinguishes good decisions from poor ones. The lowest-rated BI item, relevance of information to decision needs (BI5 = 3.61), supports this interpretation, because it shows that the remaining gap lies in the content of information rather than in its speed.

Of all predictors of decision quality, dynamic capabilities have the largest coefficient (H5; 0.417). This provides empirical evidence for a link that has so far been argued mostly in theory (Adner & Helfat, 2003; Helfat & Peteraf, 2015; Teece, 2007), and it is consistent with Shamim et al. (2019). Through sensing, managers get a clearer picture of their situation; through seizing, resources go to the option that has been chosen; and through reconfiguring, decisions stay relevant when conditions change. The strongest indicator of decision quality, consistency with long-term strategy (KM4), supports this explanation, since keeping decisions in line with strategy is precisely what seizing and reconfiguring are for.

Part of the effect of dynamic capabilities on decision quality goes through speed (H6b; indirect effect 0.115, p = 0.043), but the direct effect (0.417) is much larger, which means that adaptive companies make better decisions mainly because they understand their situation and follow up their decisions, and only partly because they decide faster. Read together with the result for BI, where the indirect effect through speed is not significant, this shows that the two antecedents depend on speed to different degrees; the answer to the question in the title is therefore that speed matters, but less than the content of information and the organization's capacity to act on it.

Conclusion

This study examined the effect of business intelligence and dynamic capabilities on managerial decision quality, with decision-making speed as a mediator, using data from 157 managers of manufacturing companies in Banten Province. The results answer the research

P-ISSN 2828-4976
E-ISSN 2808-263X

problem as follows: business intelligence (0.390) and dynamic capabilities (0.505) increase decision-making speed; business intelligence (0.250), dynamic capabilities (0.417), and decision-making speed (0.228) improve managerial decision quality, with dynamic capabilities as the strongest predictor; and decision-making speed partially mediates the effect of dynamic capabilities (0.115), whereas the effect of business intelligence on decision quality is direct. The model explains 72.7% of the variance in decision-making speed and 70.6% of the variance in managerial decision quality.

Theoretically, this study contributes to the management accounting and information systems literature in three respects: the model that combines contingency theory and the dynamic capability view (Otley, 2016; Teece, 2007) explains more than 70% of the variance in managerial decision quality; the two antecedents follow different paths, since dynamic capabilities work partly through speed while BI works directly, which clarifies how capabilities are converted into better decisions (Trieu, 2017); and the study provides a direct empirical test of the relationship between dynamic capabilities and decision quality, which earlier work had discussed mainly at the conceptual level (Adner & Helfat, 2003; Helfat & Peteraf, 2015).

In practice, manufacturing managers should direct BI investment toward the quality, relevance, and integration of information, since these aspects, rather than speed, explain the contribution of BI to decision quality (0.250), and since information relevance received the lowest score among the BI items (BI5 = 3.61). At the same time, the ability to monitor the environment, seize opportunities, and adapt had the strongest effects on both decision quality (0.417) and decision-making speed (0.505), so companies that invest in technology without building these organizational capabilities are unlikely to obtain the full benefit of their BI systems.

This study has several limitations. First, the cross-sectional design limits causal conclusions, and longitudinal data are needed to observe how the relationships change over time; second, all variables were reported by the same respondents at the same time, so common method bias may be present, and although collinearity remains acceptable, future studies could use multiple data sources or separate the timing of measurement (Podsakoff et al., 2003). Third, the HTMT values (0.887 to 0.975) exceed the conservative threshold of 0.85 (Henseler et al., 2015) and the SRMR (0.081) is slightly above 0.08, showing that constructs that are closely related in theory also overlap empirically, so future studies should sharpen the wording of items. Fourth, because only manufacturing companies in Banten Province were surveyed, generalization of the results to other sectors or regions requires caution.

Acknowledgment

The authors thank the Faculty of Economics and Business, Universitas Sultan Ageng Tirtayasa (FEB Untirta), which funded this research under its 2026 Penelitian Dosen Pemula (PDP) grant.

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