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Digital Technology Capabilities and Strategic Effective Decisions: Investigating the Mediating Influence of Decision Support Systems

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ABSTRACT

The study tested the effect of digital technology capabilities on strategic effective decisions with mediating role of the decision support system. Used cross sectional research design where quantitative data was collected from 350 employees using a self-administered questionnaire. The results showed that business intelligence, artificial intelligence, and cloud computing have significant influence on the strategic effective decisions. Decision support system also significant effect to the strategic effective decisions. Further indirect effect results shown that decision support system partially mediated among business intelligence, artificial intelligence, and cloud computing and strategic effective decisions. The study with these findings suggested that manufacturing should proper improve their strategic decisions quality through properly adopting an effective digital ecosystem where business intelligence enables data interpretation, artificial intelligence provides predictive intelligence. On the other hand, cloud computing increases the real time accessibility and then DSS helps to consolidate these effects in improving structured decision-making process which increase the company's competitive advantage.

1. Introduction

In the current rapidly evolving digital economy, companies are operating in a very uncertain and data-intensive environment where strategic decision-making quality determines the companies long term competitive advantage [1]. Accordingly, strategic effective decisions (SED) have become a key construct for companies because SED determine how effectively firms respond to environmental uncertainty and allocate resources for long-term sustainability [2]. This is the reason, SED are particularly important in in the manufacturing industry, because they directly influence production planning, inventory optimization, quality control, supply chain management, and resource allocation [3]. These decisions determine how efficiently organizations can respond to market fluctuations, technological changes, and operational disruptions [4]. In this regard, this study focused on SED because it reflects the overall effectiveness of organizational decision-making systems in achieving operational and strategic goals.

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It has been highlighted in the literature that SED is strongly influenced by digital capabilities especially in industries undergoing digital transformation [5]. Other study of Chen et al. [6] also highlighted that companies which are leveraging analytics and data-driven systems achieve higher decision accuracy, which increase SED of the organizations. This is the reason, the significance of SED becomes more effective role of digital technologies like as business intelligence (BI), artificial intelligence (AI), and cloud computing, which serve as the independent variables in this study. From the digital technologies, BI plays a key role in transforming raw data into meaningful insights through reporting, visualization, and advanced analytics systems [7]. Chen et al. [6] study also define that BI as a technology-driven process that enhances decision-making through structured data analysis, while Wixom and Watson [8] study also highlighted that BI improves organizational performance through increasing information accessibility and quality. In manufacturing environments, BI enables real-time monitoring of production performance, supply chain operations, and demand forecast improves the SED accuracy [7]. Shollo and Galliers [9] further emphasize that BI supports organizational knowledge creation, which is essential for complex decision-making in uncertain environments.

Along with the BIS, further AI also increase the SED through enabling the predictive analytics, and enhancing analytical automation [10]. On the other hand, Neiroukh et al. (2025) also explained that AI systems improve decision quality by learning from data patterns and generating intelligent predictions that support complex problem-solving. Dwivedi et al. [11] study also emphasized that AI is being significantly increasing the transforms companies' decision making through enabling autonomous and intelligent systems capable of reducing human error. In other studies, it also identified that AI is being widely applied in predictive maintenance, quality inspection, production optimization, and demand forecasting. Equally, other studies also highlighted that AI improves operational efficiency, agility, and decision accuracy in manufacturing environments [12]. Equally, cloud computing is also significant predictor to improve the SED through providing flexible and real time access towards the data and various computational resources [10]. In other words, Mell and Grance [13] study also defined that cloud computing also as on demand access to share a computing resources which helps to improve the organizational efficiency. Armbrust et al. [14] highlight that cloud systems reduce infrastructure costs while improving data accessibility and computational scalability. Marston et al. [15] further argue that cloud computing enhances organizational agility and supports distributed decision-making across global networks. These prior studies showed that BI, AI and cloud computing as digital technologies play an integral role in increasing the SED and accordingly study focused on testing the influence of digital technologies to improve SED.

As BI, AI and cloud computing are important factors to increase the SED but the effect of digital technologies is being more effectively recognized when it is being integrated through effective decision support systems (DSS). Sharda et al. [16] study also highlighted that DSS significantly increases the SED through improving the data processing capabilities and reducing uncertainty in managerial decision-making. Similarly, Bondac et al. [66] study also emphasized that modern organizations increasingly rely on DSS to improve decision accuracy and operational effectiveness in dynamic environments. This is the reason, the DSS has played a critical role in structuring, and transforming a complex data in the actionable managerial understandings [17]. As DSS is important for improving the SED, literature supported that its effectiveness is improved when the organizations have effective digital technologies. For instance, Arnott and Pervan [18], and Eisenhardt and Zbaracki [19] highlighted that DSS significantly improves SED by supporting structured analysis through the digital technologies. Power [20] study also defined that DSS as interactive systems that support semi-structured and unstructured decision problems when it is being supported with the better technologies. Other study, Sharda et al. [16] also emphasize that DSS integrates analytical models, simulation, and visualization tools to enhance decision accuracy. As DSS integrates BI-generated reports, AI-based predictions, and cloud-based real-time data streams into a unified decision-making framework. Therefore, this study focused on testing the role of digital technologies on improving SED through DSS as a mediating role.

Along with significant studies on digital technologies and SED, various important gaps still existed in prior literature. Firstly, most of the existing studies examine BI, AI, and cloud computing independently rather than integrating them into a unified decision-making framework [6; 8; 11]. This shows the importance of understanding how digital technologies affect the SED in a unified model because prior studies on AI, BI and cloud computing were mainly focused on different frameworks with a limited focus of these variables in one model. Second, although DSS has been widely studied, it's mediating role between advanced digital technologies and strategic decision-making remains underexplored [18, 66]. Therefore, this study contributed DSS as a mediating to fill the prior studies gap. Thirdly, existing research is heavily concentrated in developed economies, while limited empirical evidence exists from emerging economies, particularly in manufacturing sectors undergoing digital transformation [5]. Fourthly, although the prior studies focused on industry 4.0 where studies highlighted that significance of BI, AI and cloud computing in the context of technology adoption rather than focusing on increase SED framework [12; 21]. Finally, prior studies often ignore the structural relationships among digital technologies, resulting in a lack of comprehensive models explaining how these technologies interact to enhance strategic decision outcomes. To address the previous gaps, study focused on testing the impact of digital technologies on SED with mediating effect of DSS in manufacturing companies.

The study covering the above objective is contributing that BI, AI, and cloud computing become a strategic organizational resource which increases the company's competitive advantage. These resources generate value only when effectively deployed through organizational capabilities such as DSS. Therefore, this study contributing that DSS acts as a capability enabling organizations to sense BI, AI, and transform (Cloud-enabled DSS integration) information into strategic actions. This strengthens the theoretical understanding of how digital ecosystems contribute to decision effectiveness in manufacturing organizations. Furthermore, practically, study contributed that firms should have proper investment in the BI systems to enhance data-driven insights and performance monitoring. AI technologies should be adopted to improve predictive analytics, automation, and operational intelligence. Cloud computing infrastructure should be implemented to enable real-time data integration and scalability. The study was further divided into four various sections.

2. Literature Review and Hypothesis Development

2.1 Business Intelligence and Strategic Effective Decisions

Business intelligence (BI) consisted of different technologies and applications which helps to the companies for improving management decisions [10]. BI helps in transforming the raw data into the information that helps to the managers in improving their decision making process [22]. On the other hand, companies are totally relying on the BI systems to support strategic planning and improve decision quality [10]. Strategic decisions effectiveness (SED) often involve uncertainty, complexity, and long-term organizational consequences, making accurate information and analytical capabilities essential for effective decision-making [23]. BI played an integral role to improve the SED through providing an effective information to the managers [24]. BI systems address this challenge by integrating data from multiple sources and presenting it in a format that facilitates managerial interpretation and action [9]. Elbashir et al. [22] empirically found that BI capabilities improve managerial decision-making through enhanced information quality and management control systems. Their findings indicate that organizations possessing strong BI capabilities are better equipped to utilize organizational knowledge for strategic purposes. Visinescu et al. [25] study also further reported that BI significantly improves decision quality through increasing the availability, accuracy, and relevance of information used during decision-making processes. Urumsah and Ramadhansyah [26] study also reported that BI management quality and information quality positively influence decision-making effectiveness. Abu-Alsondos [27] study further demonstrated that BI systems improve the quality of strategic decision-making among senior managers by enhancing analytical efficiency and information accessibility. Altarawneh [67] also similary found that BI tools contribute significantly to strategic decision effectiveness through strengthening organizational ambidexterity and enabling firms to respond more effectively to environmental changes. These prior studies showed that BI is an integral factor to improve strategically effective decisions and accordingly hypothesis is,

H1: Business intelligence has a significant effect on strategic effective decisions.

2.2 Artificial Intelligence and Strategic Effective Decisions

Artificial intelligence consisted of computer based system which helps to performance various tasks from human intelligence in a modern way [10]. Various AI technologies have transformed organizational decision-making by enabling firms to analyze vast amounts of structured and unstructured data [28]. With the passage of time, AI significance in improving SED is being stems from their ability to process large datasets rapidly and generate predictive insights [29]. Other study also identified that AI always helps to address the better decision making through identifying hidden patterns, forecasting future outcomes, and generating recommendations that support managerial judgment [30]. Wamba et al. [31] study also found that data analytics capabilities, which are often powered by AI technologies, significantly improve organizational performance and decision quality. Mikalef et al. [5] study also found that AI-driven analytical capabilities positively influence organizational innovation and strategic responsiveness. Vrontis et al. [28] study also found that AI technologies enhance organizational decision-making through improving forecasting accuracy and reducing decision uncertainty. Nara et al. [32] study also found that AI-driven decision support systems significantly improve strategic decision effectiveness through intelligent which increases the SED. Other study also found that AI is one of the major factor to improve recommendations and predictive analysis. Csaszar et al. [33] further also found that AI systems are being helped to generate strategic alternatives and evaluate investment opportunities with levels of effectiveness the SED. They also argued that further research could be conducted in the manufacturing sector to improve their SED and accordingly hypothesis is,

H2: Artificial intelligence has a significant effect on strategic effective decisions.

2.3. Cloud Computing and Strategic Effective Decisions

Cloud computing consists of delivering services on computing based which consisted of software, and processing data using internet-based platform [68]. Cloud based technologies always help the companies in providing flexible resources without requiring extensive investments in physical infrastructure [68]. In other words, cloud computing has emerged as a critical enabler of organizational agility, innovation, and decision-making effectiveness [15]. Other study highlighted that cloud computing becomes an integral factor to improve the SED with its ability to improve information accessibility and organizational responsiveness [34]. With other perspectives, cloud computing helps to perform an effective platform which helps to support collaborative decision-making through allowing stakeholders to access information simultaneously and contribute to strategic discussions regardless of location [68]. Marston et al. [15] empirically found that cloud technologies improve organizational flexibility and enable more efficient access to information resources. Alkhalil et al. [35] research also highlighted that cloud computing enhances organizational performance through improving information availability and technological adaptability. Araujo et al. [36] results also found that cloud environments improve SED through enhancing analytical capabilities and multi-criteria decision analysis tools. Gupta et al. [37] study also reported that cloud computing significantly contributes to organizational agility and strategic flexibility through enabling rapid access to information and analytical resources. They also emphasized that organizations should utilize cloud technologies to respond to environmental uncertainty and market changes which is only possible when the organizations have better decision making. In other studies significance impact of cloud computing has been identified in prior literature and accordingly hypothesis is,

H3: Cloud computing has a significant effect on strategic effective decisions.

2.4 Decision Support System and Strategic Effective Decisions

DSS is referred to an interactive computer based information system which integrates data, and provide user friendly software tools for supporting the managerial decisions in the unstructured problem situations [20]. It is also help to managers in evaluating the alternatives and conducting scenario based analysis which increase the SED quality in the organizations [38]. DSS in the SED is grounded in its ability to improve decision accuracy, speed, and consistency. Strategic decisions often involve uncertainty, multiple criteria, and long-term consequences, requiring analytical support beyond human cognitive capacity [38]. In other words, DSS also provided a simulations models which allows to the managers to assess various strategic alternatives before implementation which increases the managerial judgment to increase SED. Arnott and Pervan [18] empirical studies emphasized that DSS applications significantly improve organizational decision outcomes by enhancing analytical reasoning and reducing uncertainty in complex environments. Su et al. [69] study also highlighted that DSS adoption improves managerial decision efficiency and effectiveness through providing structured analytical frameworks for evaluating business problems. Al-Emran et al. [39] study also found that DSS enhances organizational knowledge management, which in turn improves decision-making effectiveness. Sharda et al. [16] results also indicated that modern DSS integrated with business analytics significantly improves strategic decision performance in organizations by enabling real-time data analysis and scenario planning. Ghasemaghaei [40] results also conducted that analytical systems like DSS improve decision quality by enhancing data interpretation and reducing information overload. These prior studies have shown that DSS enhances SED through structuring complex data into usable formats for managerial interpretation. In this regard, DSS is expected to significantly influence SED and accordingly hypothesis,

H4: Decision support system has a significant effect on strategic effective decisions.

2.5 Mediating Role of DSS

BI helps to generate larger volumes of raw information but their strategic value is dependent on how effectively this information is processed and utilized in decision-making. DSS is being act as a critical mediating mechanism that transforms BI-generated insights into actionable strategic decisions [41]. BI provides the raw analytical foundation, while DSS operationalizes this information into decision-oriented models, simulations, and forecasting tools [41]. Wieder and Ossimitz [42] study empirical highlighted that BI improves decision-making quality indirectly through enhanced DSS, confirming that BI alone is insufficient without structured DSS mechanisms. Their study also demonstrated that companies achieve higher decision effectiveness when BI outputs are integrated into decision support processes. Elbashir et al. [22] study also argued that BI enhances managerial decision-making through integrated management control systems, which function similarly to DSS by structuring analytical outputs. Arnott and Pervan [18] study findings also demonstrated that BI achieved maximum effectiveness when it is being embedded within the DSS framework, which supports the managerial interpretation and action. On the other hand, Shollo and Galliers [9] study also found that BI contributes to organizational knowing only when supported through interpretive systems that guide managerial decision-making. These findings suggest that DSS serves as the operational bridge between BI insights and strategic decision execution and accordingly following mediating hypothesis is proposed below,

H5: Business intelligence has a significant effect on strategic effective decisions through the mediating effect of decision support system.

AI increases the company's decision making through providing predictive analytics, and machine learning models. As the AI outputs are being required a structured interpretation and integration into decision-making processes [43]. To improve this, DSS is being serve as the intermediary mechanism through which AI capabilities are translated into strategic decision effectiveness [44]. Nara et al. [32] study empirically found that AI integrated DSS always significantly increases the SED through improving predictive accuracy and decision consistency. Their study also shown that AI increase the DSS analytical capabilities, enabling managers to evaluate complex strategic scenarios more effectively. Wang et al. [30] research also demonstrated that AI-based analytics systems improve organizational DSS through reducing uncertainty and enhancing data interpretation, which helps to increase the SED. On the other hand, Csaszar et al. [33] study also provided that AI systems can generate strategic alternatives and evaluate investment decisions, but their effectiveness increases when embedded within structured decision-support frameworks. This shows that DSS played an integral role in operationalizing AI outputs into actionable strategic decisions. Furthermore, Mikalef et al. [5] results also found that AI-driven analytics capabilities improve organizational innovation through enhanced dynamic capabilities, which are often embedded in DSS architectures. Other study also highlighted, when the companies has better AI then it leads to improve the DSS because it enables organizations to transform data-driven insights into effective strategic actions [45]. Consequently, DSS mediates the relationship between AI and strategic effective decisions and accordingly hypothesis is,

H6: Artificial intelligence has a significant effect on strategic effective decisions through the mediating effect of decision support system.

In the organizations, cloud computing always provided a better infrastructure for storing the data, processing and sharing effective information which always enable to the organizations in accessing real time information in various geographical and functional boundaries [46].Literature highlighted that cloud infrastructure not only guarantee the effective SED unless it is being integrated along with the structured DSS because the DSS played an integral role through converting cloud-based data into analytical insights and decision models. Araujo et al. [36] study empirically found that cloud computing increases SED when combined with multi-criteria decision analysis systems, which are core components of DSS. Marston et al. [15] study also highlighted that cloud computing improves organizational agility and decision responsiveness, particularly when integrated with analytical decision frameworks. On other hand, Alkhalil et al. [35] study also found that cloud adoption improves organizational performance through enhanced information accessibility and technological flexibility, which strengthen DSS capabilities. Gupta et al. [37] study also demonstrated that that cloud-based systems significantly enhance SED by enabling real-time analytics and collaborative decision environments. In another study also found that DSS provides the cognitive and analytical layer required for interpreting data. Together, they enable organizations to improve strategic responsiveness and decision effectiveness [47]. These prior studies emphasized that DSS could significantly mediate the relationship between cloud computing and SED.

H7: Cloud computing has a significant effect on strategic effective decisions through the mediating effect of decision support system.

2.6 Integrated Theoretical Framework

The research framework of the study is grounded on two theories namely Resource-Based View (RBV) and Dynamic Capabilities Theory. In the framework below, BI, AI and cloud computing represents the technologies capabilities, while the DSS represents the organizational capability which enables the companies to effectively utilize these resources. On the other hand, strategic effective decision-making is the endogenous variables of integrating technological resources with analytical decision-support capabilities. Literature supported that when the companies effectively combine BI, AI, cloud computing, and DSS are better able to sense environmental changes, process complex information, and respond with effective strategic actions. Overall, the integrated framework in Figure 1 shows how digital technology capabilities translated into improved managerial decision-making effectiveness in the manufacturing sector.

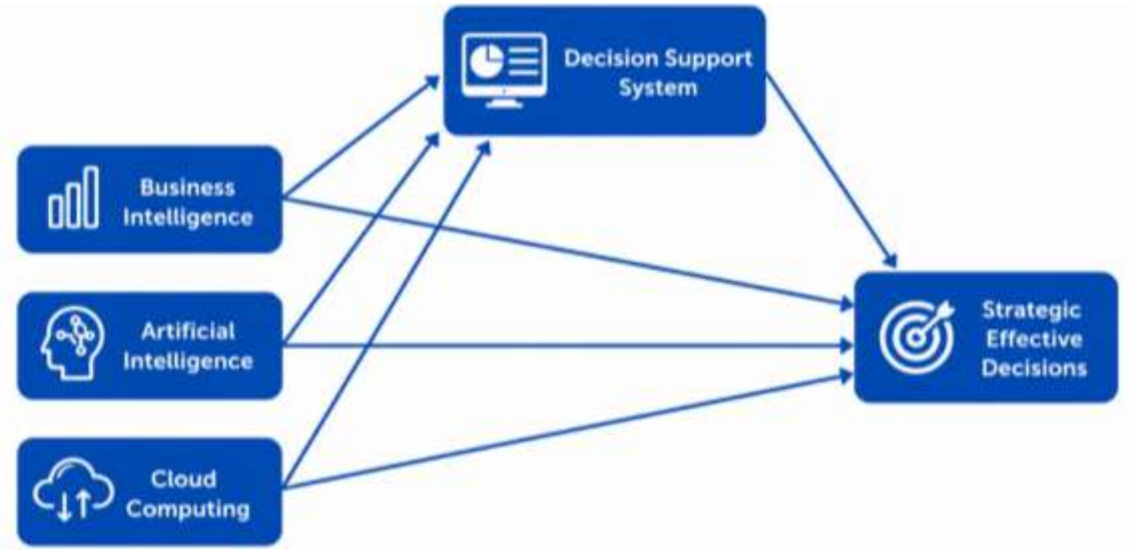

Fig.1: Research Framework

3. Research Methods and Survey Instruments

The study focused on testing the impact of digital technologies on SED with the mediating effect of DSS in manufacturing companies. A quantitative approach was used to test the study objective. The core reason for choosing this approach is because it provided a systematic, objective, and statistically rigorous method for examining relationships among variables and testing hypotheses. As compare to qualitative research approach which focused on only on experiences, and perception using less sample while a quantitative research enables researchers to collect data from a larger population, generalize findings, and establish the strength and significance of relationships among constructs through statistical analysis [48; 49]. On the other hand, this research is being employed a cross sectional research design because it allows that data will be collected from the respondents at one point [50]. Compared to longitudinal research, which requires repeated observations over extended periods and often involves substantial time and financial resources, cross-sectional designs enable researchers to obtain timely insights into organizational phenomena and are widely used in business and management research for theory testing and model validation [51]. This is the reason, quantitative research approach and cross-sectional research design is more effective for the current study.

Study population was the employees who were working in manufacturing companies who were actively involved in the operational, managerial, and strategic decision-making activities. Sekaran and Bougie [50] defined that population comprises all individuals who share characteristics relevant to the research objectives. From the population, data was collected using the convenient sampling technique because it allows researchers to select respondents based on their accessibility and willingness to participate, making it suitable for business and management research when time and resource constraints exist [49; 51]. There were 500 questionnaires distributed among manufacturing employees, where 350 questionnaires were returned and were useful for the analysis which showed 70% response rate. The final sample size exceeded the minimum recommendations for reliable statistical analysis and hypothesis testing [52].

Survey instrument was taken from prior studies. Strategic effective decisions was measured from five items and these items were adopted from two studies [53; 54]. Business intelligence comprised of 7 item which were adopted from Mbima and Tetteh [55]. Artificial intelligence comprises from 3 of Chen et al. [56]. Decision support system also comprised from 3 items of Alshibly [57]. Lastly cloud computing was comprised from two dimensions. First dimension is the IT infrastructure which is comprised of 7 items and lastly cloud strategy was comprised from 4 items. These dimensions were adopted from the study of Yang et al. [58]. Five point Likert scale used for analysis.

4. Data Analysis and results

4.1 Respondents Profile

This section shows the demographic profile of respondents which represents the diversion in the demographic characteristics. With respect to gender, most of the respondents are male 210 which is representing 60% response rate, and on the other hand females are 140 which is showing remaining 40% response rate. In terms of age, the largest group consisted of individuals aged 31–40 years, representing 150 respondents (42.9%), followed by those aged 20–30 years with 120 respondents (34.3%). Respondents aged 41–50 years accounted for 60 participants (17.1%), whereas only 20 respondents (5.7%) were above 50 years of age. Concerning educational qualifications, most respondents held a Master’s degree, comprising 180 participants (51.4%), followed by Bachelor’s degree holders with 110 respondents (31.4%). Respondents possessing a PhD represented 60 participants (17.2%). The above overall respondents profile shown that sample was predominantly composed of male, more educated employees and most of the respondents are middle aged which is showing the valuable insights among the respondents.

Table 1

Demographic Profile of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	210	60.0%
	Female	140	40.0%
Age	20–30	120	34.3%
	31–40	150	42.9%
	41–50	60	17.1%
	Above 50	20	5.7%
Education	Bachelor	110	31.4%
	Master	180	51.4%
	PhD	60	17.2%

4.2 Measurement Model Assessment

Structural Equation Modeling (SEM) technique employed for hypothesis testing in two models, measurement and structural. Measurement model was assessed using convergent and discriminant validity where findings confirmed the strong convergent validity of the measurement model. All factor loadings are above the recommended threshold of 0.70, which is showing that each item strongly represents its corresponding construct [52]. While the Cronbach’s Alpha values for all constructs exceed 0.70, which is also confirming internal consistency reliability. In the same vein, Composite

Reliability (CR) values are above 0.70, which is also indicated a high construct reliability. Lastly, Average Variance Extracted (AVE) values for all constructs is also exceeding the minimum threshold of 0.50, which is confirming that each construct explains more than 50% of the variance in its indicators [59]. In this regard, the measurement is being demonstrated a strong convergent validity which shows that model can be used for the structural model. Results are in Table.2.

Table 2
Convergent Validity

Construct	Items	Loadings	Cronbach's Alpha	CR	AVE
Business Intelligence (BI)	BI1	0.781			
	BI2	0.812			
	BI3	0.842			
	BI4	0.792			
	BI5	0.822	0.871	0.901	0.642
Artificial Intelligence (AI)	AI1	0.801			
	AI2	0.833			
	AI3	0.854			
	AI4	0.782			
	AI5	0.823	0.882	0.912	0.662
Cloud Computing (CC)	CC1	0.774			
	CC2	0.802			
	CC3	0.843			
	CC4	0.814			
	CC5	0.793	0.862	0.892	0.623
Decision Support System (DSS)	DSS1	0.822			
	DSS2	0.852			
	DSS3	0.884			
	DSS4	0.832			
	DSS5	0.864	0.903	0.933	0.693
Strategic Effective Decisions (SED)	SED1	0.842			
	SED2	0.862			
	SED3	0.875			
	SED4	0.823			
	SED5	0.851	0.891	0.923	0.674

4.3 Discriminant Validity (HTMT Criterion)

The discriminant validity was used to assess where the construct in the model is totally different from each other, and this ensures that each latent variable could capture a unique concept and does not overlap excessively with other constructs. The discriminant validity was comprising from Heterotrait–Monotrait (HTMT) ratio. Henseler et al. [60] explained that Heterotrait–Monotrait (HTMT) ratio is considered a superior and more rigorous method for assessing discriminant validity in PLS-SEM compared to the traditional Fornell-Larcker criterion. HTMT values below 0.85 indicate adequate discriminant validity, while values below 0.90 are acceptable in more liberal models. Below in Table.3 all values are less than 0.85 which shows the construct discriminant validity.

Table 3
HTMT Table

Constructs	BI	AI	CC	DSS	SED
BI	—				
AI	0.542	—			

CC	0.413	0.363	—		
DSS	0.384	0.212	0.504	—	
SED	0.802	0.503	0.610	0.712	—

4.4 Multicollinearity Test

The mulicollinearity is being referred to the situation in the regression analysis where two or more independent variables are being highly correlated correlated with each other. This could create a distorted result through making it difficult in determining the individual effect of each predictor on the dependent variable and it could be measured from Variance Inflation Factor (VIF) and recommended value should be less than 5. All VIF values in the model are less than 5, which indicates no multicollinearity issues among independent variables. Consequently, the structural model is statistically reliable for hypothesis testing. Above results are in Table.4.

Table 4

VIF Results

Predictor	VIF
BI	2.10
AI	2.35
CC	2.18
DSS	2.40

4.5 Structural Model

This section shows the results of hypothesis where all hypotheses are supported. From the direct effects, it has been found that business intelligence has positive and significant impact on strategic effective decisions (β = 0.21, t = 3.45, p = 0.001), which is showing that organizations using BI systems are more capable of making informed, data-driven decisions. Furthermore, artificial intelligence also showed a positive and significant (β = 0.25, t = 4.10, p < 0.001) impact on strategic effective decisions which is indicating that AI-driven analytics significantly enhance forecasting accuracy and strategic evaluation. Similarly, Cloud Computing has a significant positive effect (β = 0.19, t = 2.98, p = 0.003), highlighting its role in improving data accessibility, integration, and organizational flexibility for decision-making processes. Decision support system also demonstrated a positive and significant (β = 0.28, t = 4.80, p < 0.001) effect on strategic effective decision which is confirming its central importance in converting analytical insights into actionable strategic decisions. On the other hand, mediating effect results show that business intelligence and strategic effective decisions is partially mediated (β = 0.18, t = 3.20, p = 0.001) with decision support system. In the same vein, artificial intelligence also showed a mediating effect through DSS (β = 0.22, t = 3.95, p < 0.001). On the other hand, cloud computing also demonstrated a significant indirect through DSS (β = 0.17, t = 3.10, p = 0.002). These results show that all hypotheses are supported and results are in Table.5.

Table 5

Direct and Mediating Effects

Relationship	Coefficients	T-Statistics	p-value	Decision
BI → SED	0.210	3.452	0.001	Accepted
AI → SED	0.252	4.103	0.000	Accepted
CC → SED	0.193	2.982	0.003	Accepted
DSS → SED	0.284	4.803	0.000	Accepted
BI → DSS → SED	0.183	3.202	0.001	Accepted
AI → DSS → SED	0.222	3.953	0.000	Accepted
CC → DSS → SED	0.173	3.102	0.002	Supported

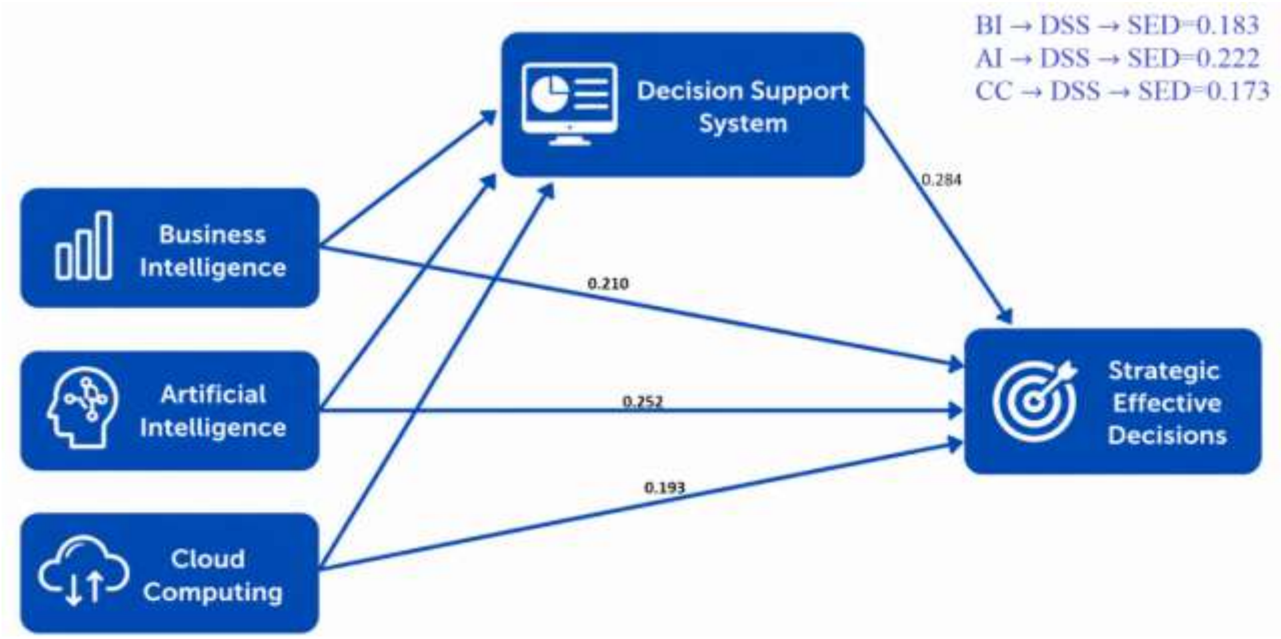

Fig.2: Beta Values

5. Discussion

Study results overall show that digital technologies, namely BI, AI, and CC significantly increase the SED from both direct and indirect effects. Various prior studies also identified that digital technologies are fundamentally transforming manufacturing decision-making structures by enabling intelligent, data-driven, and automated systems [12; 21]. From the individual effect of digital technology, it has been found that BI has a positive significant effect on strategic effective decisions. The finding shown that BI systems play a crucial role in transforming raw operational data into actionable insights for managerial decision-making in the manufacturing industry because it is being used widely for production efficiency monitoring and increasing supply chain performance. The results is supported with the study of Ahmed et al. [61] where they emphasize that BI enhances decision quality by improving data interpretation and enabling evidence-based managerial actions. Elbashir et al. [22] and Visinescu et al. [25] study also found that BI improves decision-making effectiveness through reducing uncertainty and enhancing analytical capabilities. These findings highlight that BI is an important factor for increasing production scheduling, reducing waste, and improving operational performance that could lead to improving the company's competitive advantage.

Further results reveal that AI has stronger effect on the SED compared to the other predictors and this result shows that manufacturing industry focused on the industry 4.0 where highlighted that AI is one of the core drivers of intelligent manufacturing systems. The results is consistent with the study of Csaszar et al. [33] where they demonstrated that AI significantly enhances strategic decision-making through improving search, prediction, and evaluation capabilities in complex business environments. Górka et al. [62] study results also found that AI adoption improves decision speed, accuracy, and organizational agility through reducing human error and supporting data-driven judgment. Literature also supported that AI is being increasingly applied in the predictive maintenance, defect detection, demand forecasting, and production optimization, which directly enhances strategic decision quality [10]. These prior studies confirmed that AI is not only a one of the supporting technologies but has become central enabler in the manufacturing decision making system. Study results also indicated that CC significantly increases the SED in manufacturing sector. This result shown that in the manufacturing sector, cloud computing has become a significant influence on SED from the backbone of digital manufacturing ecosystems through enabling real-time data sharing, system integration, and scalable analytics. Bastos et al. [63] found the same results where found that cloud-based systems significantly improve decision efficiency by integrating industrial internet and big data analytics for real-time production optimization. Marston et al. [15] and Gupta et al. [37] studies also confirmed that CC enhances organizational agility and supports distributed decision-making across global manufacturing networks. In Industry 4.0 environments, CC is particularly important because it enables connectivity between IoT devices, production systems, and analytics platforms, thereby improving strategic responsiveness. Thus, based on these findings it is enforced that manufacturing companies should focus on the CC to improve the SED that will lead to improving the competitive advantage.

Further effect also indicated that DSS positively and significantly increases the SED in manufacturing sector. This result highlights that DSS has become a critical factor in improving the manufacturing sector's decision-making environment, where managers must process large volumes of complex and time-sensitive data. This is supported by the prior studies where shown that DSS significantly improves operational decision-making through integrating simulation, predictive analytics, and machine learning models [12]. Bagheri et al. [64] study also shows that DSS improves production planning and resource optimization by providing structured analytical frameworks for decision-makers. Arnott and Pervan [18] also emphasize that DSS enhances decision quality by reducing cognitive limitations and supporting structured reasoning in complex environments. These prior studies emphasized that DSS acts as a critical decision layer that converts raw digital inputs into actionable strategic intelligence. In this regard, it is emphasized that manufacturing companies should be properly focused on improving their DSS, which could lead to improving the company's decision-making to improve business sustainability.

Further mediating effect results shown that DSS becomes a significant predictor for improving the impact of BI, AI, and CC into SED. This result emphasizes the significance of integration between digital technologies and structured decision frameworks. The result is supported with the previous studies where it has been identified that AI and CC significantly increase the manufacturing performance only when it is embedded within the decision support architectures that structure and interpret data outputs [12]. Araujo et al. [36] study results also found that cloud based decision also significantly improves the strategic output when it is being integrated with the DSS frameworks. Csaszar et al. [33] study also further confirm that AI-generated insights achieve maximum value when embedded in structured decision systems that guide interpretation and action. In manufacturing, DSS therefore acts as a transformation mechanism that bridges technological capability and managerial decision effectiveness. These findings are also aligned with further prior studies where it is highlighted that competitive advantage in manufacturing is increasingly determined through the ability to integrate digital technologies into decision-making structures rather than relying on traditional managerial intuition [12; 21]. In this regard, study along with the findings contributed through empirically confirming that DSS is the central mechanism through which digital technologies translate into improved strategic decision performance in manufacturing companies.

6. Implications

There are various theoretical and practical implications based on study findings. At first, study with the significant findings contributed literature with the supporting theory of RBV which shows that BI, AI, and cloud computing as strategic technological resources that enhance organizational competitiveness. Therefore, this research extended the theory through showing that organization resources lonely not increase the values of the companies until it is to be integrated with the effective DSS. This shows that DSS becomes a critical capability which converts the digital resources into strategic decision making. Secondly, study also contributed literature through supporting the dynamic capability theory through demonstrating that DSS is being acts as a sensing, seizing, and transforming mechanism. Organizations use BI and AI to sense environmental changes, CC to seize opportunities through data integration, and DSS to transform insights into strategic actions. This extends existing literature by empirically validating DSS as a core dynamic capability in manufacturing decision environments. Third, study also contributed that modern strategic decisions no longer purely cognitive or experience-based but are increasingly supported by structured analytical systems. The strong role of DSS indicates that decision quality is highly dependent on system-supported intelligence rather than individual managerial judgment alone. Finally, the study extends Industry 4.0 theoretical frameworks by integrating multiple digital technologies into a single decision-making model. It empirically validates that the value of Industry 4.0 technologies is maximized when they are integrated into DSS frameworks, thereby offering a more holistic view of digital decision ecosystems in manufacturing.

Further study results also some practical implications which are important for the manufacturing companies. Firstly, manufacturing firms should prioritize investment in BI systems to improve real-time monitoring of production processes, supply chains, and customer demand patterns. BI enables managers to make evidence-based decisions, reduce operational inefficiencies, and improve resource allocation. Second, organizations should strategically adopt AI technologies to enhance predictive decision-making capabilities. AI can significantly improve forecasting accuracy, predictive maintenance, quality control, and production optimization. This allows firms to move from reactive decision-making to proactive and autonomous decision systems. Third, the adoption of CCC infrastructure is essential for ensuring scalability, flexibility, and real-time collaboration across global manufacturing networks. Cloud systems enable seamless integration of data from multiple sources, which is critical for synchronized decision-making in complex supply chains. Most importantly, organizations must focus on strengthening DSS as the core decision-making backbone. The results clearly show that DSS is the most influential factor in strategic decision effectiveness. Therefore, manufacturing firms should integrate BI, AI, and Cloud Computing within DSS frameworks to maximize decision efficiency and reduce uncertainty in strategic planning. For policymakers, the findings suggest the need to promote digital transformation policies that support Industry 4.0 adoption, particularly focusing on analytics infrastructure, AI readiness, and cloud-based industrial ecosystems.

7. Conclusion and future Directions

Study objective was to test the effect of digital technology capabilities on strategic effective decisions with mediating role of the decision support system. The results showed that business intelligence, artificial intelligence, and cloud computing have significant influence on strategic and effective decisions. Decision support system also significantly affects strategically effective decisions. Further indirect effect results show that decision support system is partially mediated among business intelligence, artificial intelligence, cloud computing and strategic effective decisions. The study with these findings suggested that manufacturing should properly improve their strategic decisions quality through properly adopting an effective digital ecosystem where business intelligence enables data interpretation, artificial intelligence provides predictive intelligence. On the other hand, cloud computing increases the real time accessibility and then DSS helps to consolidate these effects in improving structured decision-making processes which increase the company's competitive advantage. Therefore, manufacturing firms should integrate BI, AI, and Cloud Computing within DSS frameworks to maximize decision efficiency and reduce uncertainty in strategic planning. For policymakers, the findings suggest the need to promote digital transformation policies that support

Industry 4.0 adoption, particularly focusing on analytics infrastructure, AI readiness, and cloud-based industrial ecosystems.

Study still has various limitations which need to be addressed in future study to increase the generalizability for further research. Firstly, study was limited to cross-sectional data collection where one time data collection technique was employed. As the companie's decisions making is changed over time and in this regard future research could be conducted on the longitudinal research design where data could be collected in various time frames. Secondly, study results are limited in the manufacturing sector where working environment is different from the financial or other institutions which limited the study scope. In this regard, future research could be conducted in other than manufacturing sectors to increase study scope and effectiveness. Lastly, study was focused on the survey-based data that could provide a biased response. Therefore, to remove this limitation, advanced methodologies such as machine learning-based SEM or multi-group analysis could also be applied to provide deeper insights on the top of SED on other sectors.

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