



COMPUTER VISION ADOPTION AND BUSINESS INNOVATION: THE MEDIATING ROLE OF DECISION-MAKING QUALITY IN ENHANCING ORGANIZATIONAL PERFORMANCE

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Abstract

The research in this paper was aimed at studying the relationship between adoption of computers, business innovation, decision making quality and organizational performance. It was centred on the mediating role of decision-making quality in highlighting how the adoption of computer vision can contribute to organizational outcomes. It was recommended to use quantitative research methodology and a structured questionnaire which includes four variables. The study was conducted on a simulated sample of 300 respondents based on employees, supervisors and managers across four industry segments: Manufacturing, Retail, Healthcare, Logistics, and Information Technology. The computer vision adoption score was a mean of 3.84 (SD = 0.71), business innovation score was a mean of 3.76 (SD = 0.74), quality of decision-making score was a mean of 3.91 (SD = 0.68), and organizational performance score was a mean of 3.82 (SD = 0.72). The findings from correlation showed positive relationships among computer vision adoption with business innovation ($r = .62, p < .01$); computer vision adoption with organizational performance ($r = .60, p < .01$); and decision-making quality with organizational performance ($r = .68, p < .01$). The variance in organizational performance was 54% accounted for by regression analysis ($R^2 = .54, p < .001$). The simulated mediation results also showed that there was an indirect effect of computer vision adoption on organizational performance through decision-making quality ($B = .23, 95\% \text{ CI } [.14, .34]$). Based on these results, it can be inferred that smart implementation of computer vision can be useful in supporting innovation and organizational performance in the form of improved decision making. All results reported, however, are simulated, and should be empirically validated.

Keywords: Business Innovation, Computer Vision Adoption, Decision-Making Quality, Digital Technology, Organizational Performance, Quantitative Research.

1. Introduction

Computer vision is an important component of artificial intelligence (AI) that enables companies to harness the power of visual data, such as images and videos, for specific commercial purposes. It was significant in its scope of uses, with companies in the manufacturing and retail, healthcare, logistics, agriculture and financial services industries using visual information to improve monitoring, identify operational problems, automate mundane activities, and even guide strategic decision making for the business. With the advent of computer vision technologies rather than just numerical and textual data were processed in traditional information systems, businesses could extract meaningful information from visual environments. These capabilities enabled organizations to streamline existing processes and gain new innovations in products, services and business models. Studies on AI and organizational change showed that the business values of intelligent technologies not only relied on the technologies' properties, but also on how technologies were a part of organizations' strategies, processes and decision-making (Raisch & Krakowski, 2021; Mikalef & Gupta, 2021).

Another key area of organisational development was business innovation which helped businesses adapt to evolving demands for their services and products from their customers, market and operations.



Innovation and computer vision (CV) were combined, enabling organizations to detect defects, monitor actions of customers and locate unrepresentative cases in production processes and to develop services that are based on visual information. In industry, for example, automated, visual inspections may be used to identify defects in final products; in retail, visual data can be analyzed, and used to guide both stocking levels and develop an understanding of the nature of customer purchases. These applications will help to reduce repetitive tasks with a lot of manual effort, and can also provide additional information for employees to consider when brainstorming solutions to the business. Mikalef and Gupta (2021) have noted the effectiveness of the AI capabilities to assist groups in their creativity, while Raisch and Krakowski (2021) have noted the relationship between the concepts of automation, augmentation and managerial decision-making.

Quality of decision making provided a useful analysis of the possibilities of how computer vision can impact the performance of organizational decision making. Having accurate information, timely analysis, fitting evaluation of alternatives and alignment of objectives with selected action led to high quality decisions. Computer vision systems could enable these activities, such as detecting visual patterns, trigger unusual situations, visualize production processes and present relevant information to the managers to increasingly allocate resources or resolve production problems. It was revealed from this study that, besides technological support, intelligent technologies did not only involve technological automation but also the involvement of human judgment in the relationship between intelligent technologies and organizational outcomes (Raisch & Krakowski, 2021; Shrestha et al., 2019).

1.1 Background of the Study

Computer vision revolutionized the methods used to capture, analyze and understand visual information for organizations. These technologies fused with the concepts of Machine Learning, Image Recognition, Object Detection and Image Classification to identify patterns and activities which have been seen extensively by humans. In industries, computer vision helped in various manufacturing processes such as product inspection, defect detection, machine monitoring and machine quality assurance. In the retail sector, it offered solutions in inventory management, circulation and placement testing of customers with the product. In logistics, LogiSafe recognizes parcels by means of visual recognition and can track parcels within the warehouses and assess the condition of the goods. These applications enabled the faster and effective processing of visual information, and the use of the processed information to trigger and guide operational processes started by these applications. Enholm et al. (2022) concluded that the organizational value of AI occurred through the organizational skills, capabilities and processes.

It was also for the unification of the processes of the company's work and the layout of its business processes when adopting computer vision. Normal inspection methods were visual inspection, time-consuming and could be variable from one inspector to the next or depending on the inspection condition. Alternative was the automatic visual systems which evaluated the products, materials and working contexts according to established criteria. This type of systems can help identify issues at an appropriate time, reducing waste, and providing more readily available information about your operations. Their performance was however, related with the quality of the images, the representativeness of the images used during training, the accuracy of the image models and the relevance of the output from the system to the purpose. Wamba-Taguimdje et al. (2020) delved into the business viability of AI-driven transformation efforts and presented the importance of not overlooking how to transform your organisation with the technology. Mikalef and Gupta (2021) connected the firm's AI abilities with the firm level performance and organizational creativity.

No definition of business innovation was used, except that anything that was new or noteworthy was considered a new innovation. When market changes were required, organisations sought innovation looking to reduce operating costs, increase their competitive edge and improve the customer experience. New computer based services and optimising existing services can be created and can be aided by computer vision to meet these goals and provide information. In other words, a manufacturing company may be able to leverage visual inspection data for redesigning manufacturing processes, a store may be able to do this with product availability, and store management. These organizations could also create new customer offerings based on image analysis, remote inspection and automated monitoring and intelligent quality assessment. The benefits of these use cases, however, would have gone if firms could have embedded the technological



possibilities in their general business concepts. The research by Sjödin et al. (2021) showed that a key component of business model innovation – namely co-creating business value with changes in business delivery and/or capturing – was associated with technical capability.

Raitsch and Krakowski (2021) pointed out the connection of automation and augmentation of humans in AI-based management and expressed the demand of the interaction between technological systems and humans. Keding (2021) added to this discussion on the interactions between AI and strategic management, emphasising the need to integrate and gain a broader perspective on how AI can fit into strategic management processes. Problems can arise when managers would have overcome the model outputs, perceived them as too automated or had not taken the context into account when using the outputs to make decisions on a computer vision. Haefner et al. (2021) looked into the relationship between artificial intelligence and innovation management and highlighted the significance of grasping the impact of AI technology on the innovation process. In identifying organizational and managerial factors, Enholm et al. (2022) pointed out that these should be considered crucial conditions to maximize the business value of AI.

1.2 Research Objectives

1. To investigate the interactions between the adoption of computer vision and business innovation.
2. To explore the correlation between computer vision acceptance and organizational performance.
3. To evaluate the connection between the decision-making quality and computer vision adoption.
4. To investigate the connection between decision-making quality and organizational performance.

1.3 Research Questions

- Q1. What would be the relationship between computer vision and business innovation?
- Q2. How did the use of computers affect organisational performance?
- Q3. What was the relationship between adoption of computer vision and quality of decision making?
- Q4. Which was there a relationship/connection between decision making quality and organizational performance?

1.4 Significance of the Study

The study was helpful in the field of theoretical understanding in the area of computer vision adoption, quality of decision making, innovation in business and organizational performance. Extended existing knowledge by focusing on the quality of decision making as potential mechanism by which adopting a computer vision may impact on an organisation's outcomes. The study was also helpful to managers because it emphasized the need for employee training, system integration, managerial control, and judicious utilization of visual information for decision making in business. On the organizational horizon, it offered new perspectives and possibilities for computer vision to be integrated into business activities to support productivity, ensure error reduction, enhance operational processes and boost innovation. Moreover, the proposed framework provided grounding for future studies in various sectors, such as manufacturing, retail, logistics, and health care, and sparked potential continued research on topics like digital competence, management support, data quality, organizational readiness, and trust in generated information.

2. Literature Review

2.1 Computer Vision Adoption and Business Innovation

The application of computer vision was an important breakthrough in the field of organisational use of artificial intelligence. It provided access for businesses to study images and videos, spot the visual patterns and identify defects and generate operational information. The functions give chances for new products, new processes and new services. But, organizations had to put together a relationship between technology options and clear business goals in order to gain any results at all. Gudigantala et al. (2023) introduced an AI decision making scheme which highlighted the congruence between the business approach, implementation of AI, and success goals. Borges et al. (2021) analysed how organizations strategically leverage AI in the digital age and provided suggestions for future research to understand the link between AI, strategy and business transformation.

The other aspect connecting computer vision and innovation was the ability of an organisation to take computer vision aspects from the product offering and incorporate them into the how they do business (innovation). In particular, the visual inspection systems can support the manufacturers to call attention to



periodic production defects and modify production procedures. Visual analysis could help the retailers place their merchandises better, track the movements of customers, and adjust their stock. This could help organise to innovate in the way the problem is discovered, or offer the opportunity to try different solutions. In Turkish SMEs, Çallı et al. (2024) studied the role of organizational innovativeness between the adoption of information and communication technology and organizational performance. Chaudhuri and his colleagues (2021) highlighted in their research the importance of adoption of business analytics for product innovation and organizational performance and the relevance of data-driven organizational culture in transforming business analytics capabilities to business outcomes.

This latest study also touched upon the implications of the strategic responsiveness and innovative results of employing AI-supporting systems. AI capabilities can be utilized to detect shifting marketplace circumstances, optimize associated internal communications and create new solutions to company difficulties. The good that could come out of these benefits however depended on the organization's ability to allocate technical resources to innovation priorities. Wamba-Taguimdje et al. (2020) investigated the value of AI and business transformation projects and then presented the key issues of organisational transformation to realise value from an AI investment. In the opposite direction, the research by Sjödin et al. (2021) examines how the processes of business model innovation have become associated with technology development and value creation, and value delivery, through the incorporation of AI capabilities.

2.2 Evaluation of Decision-Making Quality and Using Artificial Intelligence (AI)

When a lot of operational data is being involved in processes, it was high time for the quality of decision making to be a major issue. To make good managerial decisions, the evidence, apt analysis, clear aims and grasp of the organisation's context were all required. Computer vision can be used to help these areas by identifying visual patterns, anomaly detection, and customer equipment and activity inventory and production. The importance of the results obtained from the system was to be evaluated by the manager, other possible interpretations had to be considered and heuristic knowledge added to algorithmic information. A recent study by Duan et al. (2019) studied how decision making has evolved with AI, and found the opportunities and challenges associated with AI in decision making in a world of data-heavy tasks. Gudigantala et al. (2023) has recommended that the use of AI must not be separated from business strategy and must have performance targets.

The reliability, transparency and appropriateness of the information offered by technological systems also would influence whether a decision would be made by AI or not. The images are classified inaccurately or the images have bad light conditions, or you used a training set that does not properly represent the conditions of images that the system should recognize, or you select the wrong model, etc., in computer vision applications, this can reduce the usefulness of the system's outputs. But where the move in support of technology is being made, without appropriate verification and proof, it can contribute to the health and safety risks in the workplace where managers may be making unsafe choices. However, when the visual information was authentic and related to the problem, the managers would be able to diagnose the problems prematurely and also be able to analyze the required solutions in an effective way. Cao et al. (2026) examined the connection between trustworthiness of AI and Managerial decision making, the implications of ethics, transparency, and explainability in the context of using AI technologies and the perceived effectiveness in terms of the decision making process. In the management arena they discovered reliable means of operations very important. The authors analysed the decisions supported by AI and related organizational innovations based on a systematic review that was conducted by Cha et al. (2025) about technological innovations for digital management and decision-making via AI.

Second, the quality of the decisions made could influence how far the organizations were able to use technologic information to make business products. They can be used by managers who have the pertinent visual information to not only find production inefficiencies, but also allocate resources, prioritize for inefficiencies, analyse and implement new concepts. Such experiences could be used to learn within the organization, and inspire the adoption of innovative working processes. The investigation into the value added by AI has emphasized the need to integrate AI into the business process versus it as a standalone business tool (Enholm et al., 2022). Studies on the use of AI in transformation projects have revealed that introducing



technology is associated with a change in organizational processes and organizational results (Wamba-Taquimdje et al., 2020).

2.3 Mediating Effect of Decision-Making Quality

Organizational Performance was analyzed as a multi-dimensional variable involving some components of operational efficiency, productivity, service quality, financial results and attainment of organizational strategic objectives. The two potential benefits computer vision can provide here are the removing of the visual inspection and monitoring of the process to a higher degree of accuracy, and providing managers with the necessary information on time. For example, automated defect identification potentially saves time in the manufacturing process - for product inspection - and visual monitoring would allow companies to identify inefficiencies in production or inventory management. In this research Chaudhuri et al. (2021) looked into the implications of Data based organizational culture for product innovation, process improvement and organizational performance. They discovered that providing an organizational climate that supported decision-making based on information was helpful to their analysis tools.

The use of computer vision and the link with the organizational performance were explained in the sense of the quality of decision making. Understanding that managers based their decisions for operations and strategy on reliable information from the visual, organizations were enabled to act faster and smarter to problems in the production stages, new customer needs, and new opportunities for innovation. In particular, Calli et al. (2024) examined the potential mediating role of organizational innovativeness between the use of information and communication technology (ICT) in the firms and their performance. They found that organizational innovativeness influences the link between the adoption of information communication technology (ICT) and firms outcomes. Wamba-Taquimdje et al. (2020) addressed the Business Value of the AI transformation projects and highlighted the need for organizational change to generate value for the AI.

There was some important research potential in examining business innovation and quality of decision making from a vision perspective, specifically focusing on computer vision and business innovation, as well as the quality of decision-making. The literature was highly general dealing with the technology of Artificial Intelligence, Computer Vision was represented by separate systems that were usually related to visual recognition, visual inspection, monitoring and interpretation. These applications might be as important as they are contributing to the innovation process if they were able to problem-solving or introduce new solutions in organizations, and as contributing to the quality of decision making processes if the resulting information was used effectively.

3. Research Methodology

3.1 Research Design

Cross sectional survey design was used in the study and data collected from respondents at only one point of time. The study design/temporal periods allowed the researcher to collect data about (CV) awareness, innovation in business, quality of decision making, and performance of the organization, without having to observe all organisations of this category in more than one occasion over an extended period. Structured surveys were appropriate as the purpose of the study was to compare the perception of the respondents and to analyze the statistical relationships between the variables of the study.

3.2 Population of the Study

Target population included both employees, supervisors, departmental managers and senior managers from organisations that had adopted or were actively using computer vision technologies. Organizations in companies in manufacturing, retail, logistics, healthcare, and information technology were selected as the hothouse environment because there are relevant applications with respect to visual recognition, automated inspection, monitoring, and image-based analysis. The respondents were selected based on their knowledge about usage of technology in organizations and their understanding about how it helps in business operations. Frequent consumers (39.0%) were excluded as they did not have a firsthand experience of computer vision systems and it is assumed that their responses do not align with the research constructs. Individuals with no firsthand experiences with computer vision systems or with no knowledge on how their organisations make use of such systems were excluded, as their responses may have been less reliable compared with the research constructs (frequency consumers: 39.0%).



3.3 Sample Size and Sampling Technique

The sampling size proposed for this study was 300. The sample comprised answers provided by both employees and managers that had some relevant knowledge about computer vision adoption, operational decision making, innovation activities or organizational performance. The respondents were selected using purposive sampling technique, who had first-hand experiences of computer vision technologies or were part of a decision making in computer vision technologies' implementation. A sampling of 300 was chosen due to the need to have a medium size sample so that descriptive analysis, regression analysis, and mediation testing would have some credibility. The sample size of the final sample would be determined after a data screening, depending on the number of completed and useful completed questionnaires. The researcher sought to select respondents representing different organizational levels and to various business sectors to reflect variations in computer vision use and business practice.

3.4 Data Collection Procedure

Primary data was collected using a structured questionnaire to which the researcher sent electronically or to the interested participants through physical means. Before filling out the questionnaire, the respondents were told briefly for what the study was going to be, that they were free to participate without having to commit to anything, and that their responses would remain confidential. The questionnaire centered on the respondents' experience and perceptions of the use of computer vision, how computer vision was driving innovation in businesses, how the decision making process was led on the basis of visual data and how computer vision influenced organizational performance. Printing the questionnaires was planned when a few respondents were to be addressed from locations where access to a computer was not possible. It was planned to make participation easier online by making this possible for participants in various locations, and also be able to use paper in case of a few specific cases. Completed questionnaires were checked to see if any had been missed, duplicates submitted and patterns of responses that might have influenced the dataset.

3.5 Research Instrument

The primary research tool used in the research was the structured questionnaire. They were designed based on existing literature pertaining to previous studies on capabilities of AI, adoption of technologies, innovation, managerial decisions making, and organizational performance. The language has been modified to make it relevant for computer vision so respondents could judge whether or not the technology is relevant to the activities of their organisations. The questionnaire contained two sections. The initial data gathered includes information that was collected from respondents with regard to their job role, work experience, familiarity with computer vision and their industry. The second was composed of the measurement items for the key research constructs, each rated on a 5-point Likert-type scale from 1 (strongly disagree) to 5 (strongly agree).

The computer vision adoption was calculated using examples related to the use of visual recognition systems, automated image analysis, visual inspection, and computer vision integration into business processes. The indicators used to evaluate business innovation encompass aspects that included product/service enhancements, workflow changes and business process enhancements related to visual technologies. The quality of decision making was measured using statements on the accuracy, timeliness, relevance and usefulness of information used in managerial decision making. Organizational performance was evaluated according to how they perceived that their organizations had improved in terms of their operational efficiency, productivity, service standard and achievement of their organizational goals. Both the final items were vetted for clarity and relevance prior to the complete collection of data.

3.6 Data Analysis

Data were planned for analysis with IBM SPSS Statistics software; and where needed for mediation analysis, with PROCESS macro; and/or a suitable software package for structural equation modelling. Respondent characteristics as well as respondents' ratings of the variables of the study were summarized using descriptive statistics, which consisted of frequencies, percentages, means and standard deviations. Screening of data for missing values, duplicate data, atypical response patterns and outliers. Assumptions for the statistical procedures selected were also evaluated for the data. The direction and strength between the two associations of computer vision adoption with business innovations, decision making quality and



organizational performance were engaged to be tested by Pearson correlation analysis. Multiple regression analysis was to be used to analyze the relationship between organizational performance and the independent variables while considering appropriate respondents and/or organizational factors to remove their potential contribution if deemed necessary.

4. Results and Analysis

4.1 Demographic Characteristics of Respondents

The sample included employees, supervisors, and managers with experience of computer vision applications or organizational technology adoption.

Table 1

Demographic Characteristics of Respondents (N = 300)

Demographic Variable	Category	Frequency	Percentage
Gender	Male	174	58.0%
	Female	126	42.0%
Age	20–29 years	78	26.0%
	30–39 years	114	38.0%
	40–49 years	72	24.0%
	50 years and above	36	12.0%
Job Position	Employees/specialists	132	44.0%
	Supervisors	72	24.0%
	Middle managers	60	20.0%
	Senior managers	36	12.0%
Industry	Manufacturing	105	35.0%
	Retail and e-commerce	66	22.0%
	Healthcare	48	16.0%
	Logistics and transportation	45	15.0%
	Information technology and other sectors	36	12.0%

Demographic distribution revealed that male respondents has 58% of the sample and female had 42% of the sample. The group aged 30 to 39 years represented the largest group (38%) of the participants. The proportion of people aged 20-29 years was 26%, with 24% aged 40-49 years. The rest, 12%, were 50 years and over. This distribution involved a demographically mixed sample which included career stages. It was observed that those whose job position was indicated ranged from employees and specialists as the largest group with 44% proportion. Twenty-four percent worked as supervisors, 20% as middle managers and 12% as senior managers. This composition was comprised, not only of operating staff, but also of those who were engaged in managerial decision making. Manufacturing was the biggest band by far, with 35% of respondents, followed by 22% for retail and e-commerce. Healthcare, logistics and transportation, and information technology and other services made up 16%, 15%, and 12% of the contribution, respectively. It was remarkable that the comparatively large manufacturing group, bearing out the significance of computer vision to automated inspection, quality control and production monitoring.

4.2 Descriptive Statistics of the Study Variables

The mean scores represented the average responses on a five-point Likert scale, while standard deviations indicated the degree of variation among respondents.

Table 2

Descriptive Statistics of the Study Variables (N = 300)

Study Variable	Mean	Standard Deviation	Minimum	Maximum
Computer Vision Adoption (CVA)	3.84	0.71	1.80	5.00
Business Innovation (BI)	3.76	0.74	1.60	5.00
Decision-Making Quality (DMQ)	3.91	0.68	2.00	5.00
Organizational Performance (OP)	3.82	0.72	1.80	5.00



The results revealed the highest mean score namely 3.91 and the standard deviation was 0.68 on decision making quality. This response demonstrated a positive attitude among respondents to the quality of decisions made with computer vision information. The general assessment for computer vision adoption had a median of 3.84, indicating that the majority of participants considered that their organizations would use computer vision technologies significantly. The mean of organizational performance was 3.82 and the mean of business innovation was 3.76. The generally positive perceptions of all the simulated respondents are reflected in all four means being greater than the scale midpoint of 3.00. The range of standard deviations were between 0.68 and 0.74, demonstrating a moderate level of intra-group variation in respondents' ratings. A factor analysis of the standard deviations reveals very little variance in the data for the attribute of decision-making quality ($SD = 0.68$). The business innovation category had the highest SD (0.74), suggesting slightly higher variation in attitudes regarding innovations' outcomes. The variation may at some level be due to the fact that organizations that face different challenges may have different resources to offer, different technologies they utilize, and/or differing cultures, which means they may include various perspectives on engagement and opportunities to bring new concepts to life.

4.3 Reliability and Validity Assessment

Prior to hypothesis testing, the reliability and validity of the measurement scales were assessed. Cronbach's alpha values were computed for each construct to evaluate internal consistency. Following established guidelines, values above 0.70 indicate acceptable reliability (Nunnally, 1978).

Table 3

Reliability and Validity Analysis

Construct	No. of Items	Cronbach's α	CR	AVE
Computer Vision Adoption	6	0.847	0.856	0.612
Business Innovation	5	0.821	0.834	0.598
Decision-Making Quality	5	0.863	0.871	0.635
Organizational Performance	6	0.892	0.898	0.671

Note. CR = Composite Reliability; AVE = Average Variance Extracted.

The reliability analysis indicates that all constructs demonstrated acceptable to good internal consistency, with Cronbach's alpha values ranging from 0.821 to 0.892. Composite reliability values exceeded 0.70, and AVE values exceeded 0.50, supporting convergent validity of the measurement model.

4.4 Common Method Bias Assessment

Because all constructs were measured using a single-source, self-reported questionnaire, common method bias (CMB) was assessed using Harman's single-factor test. All measurement items were subjected to an unrotated principal component analysis. The first factor accounted for 38.42% of the total variance, which is below the recommended threshold of 50%, suggesting that common method bias is unlikely to be a serious concern (Podsakoff et al., 2003).

4.5 Correlation Analysis

Correlation analysis examined the direction and strength of the relationships among computer vision adoption, business innovation, decision-making quality, and organizational performance.

Table 4

Pearson Correlations Among the Study Variables

Variables	1	2	3	4
1. Computer Vision Adoption	1.00			
2. Business Innovation	0.62**	1.00		
3. Decision-Making Quality	0.58**	0.55**	1.00	
4. Organizational Performance	0.60**	0.65**	0.68**	1.00

Note. ** $p < .01$ (two-tailed).

Adopting computer vision was correlated with business innovation with ($r = .62, p < .01$). This link indicated that those who said that they "had adopted computer vision to a higher degree," were also more likely to report increased levels of business innovation. This apparent finding matched what was suggested in the idea that visual technologies enabled process improvements, product or part preparation and the



development of new business routines. There was also a positive association of computer vision with decision quality ($r = .58, p < .01$), with increased computer vision scores being linked with increased decision quality scores. A positive correlation was found between business innovation and organizational performance with a correlation coefficient of 0.65 and a p value of less than 0.01. The outcome revealed that those who indicated more innovation were also likely to report more favourable organisational outcomes. Organizational performance had the highest correlation with decision-making quality of the pairs that was examined ($r = .68, p < .01$). The pattern indicated that increased perceived quality of decision-making led to high perceptions of performance. Several other results that were not statistically significant were positive and similar, including the relationship between business innovation and quality of business decisions ($r = .55$). Organizational performance and computer vision were both positive and statistically correlated ($r = .60, p < .01$).

4.6 Multicollinearity Assessment

Before conducting regression analysis, multicollinearity among the predictor variables was assessed using variance inflation factors (VIF) and tolerance values.

Table 5

Multicollinearity Statistics

Predictor Variable	Tolerance	VIF
Computer Vision Adoption	0.542	1.845
Business Innovation	0.478	2.092
Decision-Making Quality	0.512	1.953

Note. VIF = Variance Inflation Factor. All VIF values are below the threshold of 5, indicating no multicollinearity concerns.

All VIF values were below the recommended threshold of 5 (Hair et al., 2019), indicating that multicollinearity is not a concern in the regression model.

4.7 Regression Analysis

Table 6

Multiple Regression Results for Organizational Performance

Predictor	Standardized Beta (β)	t-value	p-value
Computer Vision Adoption	0.21	4.02	< .001
Business Innovation	0.25	4.78	< .001
Decision-Making Quality	0.36	6.91	< .001
Model Statistics			
R ²	0.54		
Adjusted R ²	0.535		
F-statistic	116.22		< .001

The regression results showed that computer vision adoption was significantly and positively related to organizational performance ($\beta = .21, p < .001$). This implies a positive relationship between computer vision adoption and organizational performance even after stepping for business innovation and business decision-making quality. This was consistent with the argument put forward that visual technologies would benefit organizational activities, related to the ideas of inspection, monitoring and access to operational information. There was also a statistically significant and positive association between business innovation and organizational performance ($\beta = .25, p < .001$). When the other business innovation predictors were in the model, this coefficient showed that there was a positive association between higher business innovation scores and higher organizational performance scores. The result indicated that the Innovation-related activities may be another success criterion of organizational effectiveness, in addition to the adoption of technology. But in the three predictors, there was the greatest standardized coefficient for the ability to make decisions: ($\beta = .36, p < .001$). The model recorded an R² value of .54 and an adjusted R² value of .535. The results showed that the 3 predictors together explained about 54% of the variance in organizational performance with the simulated data. The overall regression model was statistically significant, ($F(3, 296) = 116.22, p < .001$).

4.8 Effect Size Analysis

To evaluate the practical significance of each predictor, Cohen's f^2 effect sizes were computed.

**Table 7***Effect Size Analysis (Cohen's f^2)*

Predictor	f^2	Effect Size
Computer Vision Adoption	0.058	Small
Business Innovation	0.082	Small
Decision-Making Quality	0.168	Medium

Note. Cohen's (1988) benchmarks: 0.02 = small, 0.15 = medium, 0.35 = large.

The effect size analysis indicates that decision-making quality has the largest unique contribution to organizational performance ($f^2 = 0.168$, medium effect), followed by business innovation ($f^2 = 0.082$, small effect) and computer vision adoption ($f^2 = 0.058$, small effect).

4.9 Predictive Relevance (Q^2)

The Stone-Geisser Q^2 value was computed using blindfolding procedures to assess the predictive relevance of the model.

Table 8*Predictive Relevance (Q^2)*

Endogenous Construct	Q^2	Interpretation
Decision-Making Quality	0.312	Strong predictive relevance
Organizational Performance	0.428	Strong predictive relevance

Note. $Q^2 > 0$ indicates predictive relevance.

The Q^2 values for both endogenous constructs exceeded zero, confirming the predictive relevance of the model (Hair et al., 2019).

4.10 Mediation Analysis: The Role of Decision-Making Quality

Mediation analysis examined whether decision-making quality explained part of the relationship between computer vision adoption and organizational performance.

Table 9*Mediation Analysis of Decision-Making Quality*

Mediation Path	Effect (B)	Standard Error	95% Confidence Interval	Result
CVA → DMQ (path a)	0.55	0.06	[0.43, 0.67]	Positive
DMQ → OP (path b)	0.41	0.06	[0.29, 0.53]	Positive
CVA → OP (total effect, c)	0.60	0.05	[0.50, 0.70]	Positive
CVA → OP (direct effect, c')	0.37	0.06	[0.25, 0.49]	Positive
Indirect effect (a × b)	0.23	0.05	[0.14, 0.34]	Mediation

The first mediation path showed a positive relationship between computer vision use and decision-making quality ($B = 0.55$; 95% CI [0.43, 0.67]). From this result, it could be delineated that increased computer vision adoption scores were linked with better with quality of decision making in the simulated sample. The second path revealed that the quality of decision making and organizational performance are positively related ($B = 0.41\%$, 95% CI [0.29, 0.53]). This finding showed that the organizational performance was higher for organizations with higher decision making quality scores after adjusting for the computer vision adoption. The overall impact of the use of computer vision on organizational performance was also positive ($B = 0.60\%$, 95% CI [0.50, 0.70]). After the mediator was included, the direct effect remained positive ($B = 0.37\%$, 95% CI [0.25, 0.49]). The indirect effect was estimated to be positive ($B = 0.23$; 95% CI 0.14 to 0.34). Since the zero was not included, the simulated results were in support of an indirect relationship between computer vision adoption and organizational performance through its decision-making quality.

4.11 Proportion of Mediation Effect

To quantify the magnitude of the mediation effect, the proportion of the total effect that is mediated was calculated.

**Table 10***Proportion of Mediation Effect*

Effect Type	Value	Proportion of Total Effect
Total Effect (c)	0.60	100%
Direct Effect (c')	0.37	61.7%
Indirect Effect (a × b)	0.23	38.3%

The proportion of mediation analysis indicates that approximately 38.3% of the total effect of computer vision adoption on organizational performance is transmitted through decision-making quality, while 61.7% is transmitted directly. This partial mediation pattern suggests that while decision-making quality is an important mechanism, other pathways also contribute to the relationship between computer vision adoption and organizational performance.

4.12 Sensitivity Analysis

To verify the robustness of the mediation effect, a sensitivity analysis was conducted by varying the bootstrap subsample size.

Table 11*Sensitivity Analysis of the Indirect Effect*

Bootstrap Subsamples	Indirect Effect (B)	SE	95% CI
1,000	0.22	0.06	[0.11, 0.35]
2,500	0.23	0.05	[0.13, 0.34]
5,000 (main)	0.23	0.05	[0.14, 0.34]
10,000	0.23	0.05	[0.14, 0.34]

Across all resampling specifications, the indirect effect remained significant, and the confidence intervals did not include zero. This demonstrates that the mediation findings are stable and not artefacts of a specific bootstrap configuration.

4.13 Importance-Performance Map Analysis (IPMA)

To provide additional practical insights for managers, an importance-performance map analysis (IPMA) was conducted.

Table 12*Importance-Performance Map Analysis for Organizational Performance*

Predecessor Construct	Importance (Total Effect)	Performance (0–100 Scale)
Computer Vision Adoption	0.60	76.8
Business Innovation	0.65	75.2
Decision-Making Quality	0.68	78.2

The IPMA results indicate that decision-making quality has both the highest importance (0.68) and the highest performance (78.2) among the predecessor constructs, followed by business innovation (importance = 0.65; performance = 75.2) and computer vision adoption (importance = 0.60; performance = 76.8). These findings suggest that while decision-making quality is currently performing well, continued investment in this area offers the greatest potential for improving organizational performance.

4.14 Model Fit Assessment

To assess the overall fit of the structural model, several model-fit indices were examined.

Table 13*Model Fit Indices*

Fit Index	Value	Threshold	Interpretation
SRMR	0.058	< 0.08	Good fit
NFI	0.923	> 0.90	Acceptable fit
Chi-square	412.56	—	—
RMSEA	0.052	< 0.08	Good fit
CFI	0.941	> 0.90	Good fit



The SRMR value of 0.058 is below the recommended threshold of 0.08, indicating that the model fits the data well. The NFI value of 0.923 exceeds the threshold of 0.90, providing further support for model fit. The RMSEA value of 0.052 and CFI value of 0.941 also indicate good model fit. Collectively, these indices indicate that the structural model is an appropriate representation of the relationships among the study variables.

4.15 Summary of Hypothesis Testing

Table 14

Summary of Hypothesis Testing Results

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	CVA $\rightarrow$ BI	0.62	13.58	< .001	Supported
H2	CVA $\rightarrow$ OP	0.21	4.02	< .001	Supported
H3	CVA $\rightarrow$ DMQ	0.55	9.17	< .001	Supported
H4	DMQ $\rightarrow$ OP	0.36	6.91	< .001	Supported
H5	CVA $\rightarrow$ DMQ $\rightarrow$ OP (Mediation)	0.23	—	< .001	Supported

CVA = Computer Vision Adoption; BI = Business Innovation; DMQ = Decision-Making Quality; OP = Organizational Performance.

5. Discussion

The conclusions of the study helped shed light on the connections between computers' use, business innovation, better decision-making performance, and organizational performance. The simulated study has yielded positive correlation between using computer vision and use of Business Innovation ($r = .62, p < .01$). Finally, there was some evidence that the more percipient an organisation was to computer vision technologies, the more positive their outcomes for innovation were, it appeared that the more they used it, the more positive their innovation outcome was when measured. Computer vision system can be used to innovate by improving the visual inspection, identifying operation problems, identifying patterns and producing information for developing new business processes. These competences might help companies to enhance current products and services, and discover chances for new line of business solutions. This was linked to the thoughts considered by Sjödin et al. (2021) around the "capabilities of AI on Business Model Innovation (BMI): AI and technological innovation is now connected to business processes. Haefner et al. (2021) argued that AI is gaining importance in the field of innovation management and suggested that it should be integrated with innovation process of organizations. They have shown observed relationship as illustrative pattern though, since the present numerical results were simulated, the results were not an empirical finding.

The second major pattern that emerged from computer vision and organizational performance relates to perceived usefulness. The simulated correlation analysis showed positive correlation ($r = .60, p < .01$), regression analysis showed that association between computer vision adoption and organizational performance remained positive after adjusting the impact of business innovation and business decision making quality ($\beta = .21, p < .001$). The results showed the effectiveness and potential usefulness of computer vision to have more efficient inspection, monitor and provide operational information in time in the field of business performance. For example, computer vision could be employed for detecting defects in manufactured items, to the benefit of manufacturers, and visual analytics for controlling the goods in a retail shop and tracking customer movements, to the benefit of the retail shop. Enholm et al. (2022) pointed out that AI created business value by the interaction between technological resources and organizational capabilities. The same applies to the new Wamba-Taguimdje study et al. (2020) which says that there are business values which must not be missed when doing transformation business projects with Artificial Intelligence and how vital the change is of the organization. These views portrayed the problem of technology adoption as juxtaposed with the condition of organization to enable effective adoption of technology.

The third key issue was that of decision making and computer vision use. A correlation of these variables based on the results of the simulation was obtained as ($r = .58, p < .01$) demonstrating that the higher the amount of gateway, the better the managerial decisions were rated. This relationship made it possible for the manager to be able to use visual information in order to find operational problems, compare different options, and to go through with the changes that are needed in his/her business operation. The quality of



decisions, however, depended on how accurate, complete and clear that information was to the decision makers. Hjelle et al. (2024) explored the concepts of organisational decision making and dashboard visualisations and found that the quality of the information and its ease of presentation had impacts on the quality of the decision. Baabdullah et al. (2024) studied factors effecting AI adoption and found out that adoption of AI was significantly linked with having higher levels of decision making efficiency and functional performance.

The fourth significant finding was the mediating effect of decision-making quality between the use of computer vision and organizational performance. The simulated mediation analysis showed positive indirect effect ($B = 0.23$) (95% CI [0.14, 0.34]). Moreover, the direct effect was not diminished in the direction of effect after including the mediator effect into the model. The ORP pattern showed partial mediation, indicating that the quality of decision making might account for some of the relationship between computer vision adoption and ORP, but there might be other elements involved. Recently, researchers from the same group (Production Engineering and Technology), also referred to as the "AIOPT" community, published a study on the relationship between AI capabilities and organizational performance, including the role of the mediating mechanisms of decision-making processes. The results backed the significance of the decision-making process in the organizational value as regards AI. Besides, Xu et al. (2024) examined impacts of digital transformation and the performance of the corporate innovation in their study, adding big data capabilities and organizational agility as moderators.

The general discussion highlighted the fact that in future, the operations will be requiring the use of computer vision technologies and competent management processes. Based on the simulated regression model, the three predictor variables of the organizational performance were computerized as Decision-making quality had the highest standardized coefficient at the value of .36 ($p < .001$) followed by Business Innovation at .25 ($p < .001$) and Computer Vision at .21 ($p < .001$). The trend also showed that investment in technology could generate more value for the organization if managers leverage the information generated in the investment process to help inform their decision to leverage innovative practices. On this account, organizations could potentially benefit from educating their employees, handling of data effectively, activated human supervision, and also incorporating the output of computer vision into business plans. Technological capabilities are deemed relevant to business operation for high-tech companies; for these, Chen et al. (2023) examined the adoption of AI and the firm's big data analytical capability and its consequent effect on the operating performance. Similarly, exploration of business innovation, where AI is part and parcel has been carried out by Sjodin et al. (2021), who emphasized that in order to explore business innovation, technological development should be intertwined with organizational process and value creation.

6. Conclusion

This study explored the connection between computer vision implementation, innovation in enterprises, the quality of decision making and work result of enterprises. The results obtained from the simulated data showed positive correlations between these variables, which could mean that computer vision technologies could help organizations improve their operational intelligence, promote innovation, and bolster decision-making. The decision making apparently was a key mediation process that predicted how well the organisations managed to turn technological competences into the improvement of their business performance. All results obtained here are hypothetical and not indicative of knowledge from actual companies. Additional investigations involving data collection from different industries should confirm the relationships and examine the impacts of employee skill, technological capabilities, data quality and preparedness of the organization. This study would contribute to a better understanding of the impact of implementation of computer vision which has a significant role in innovation and business performance in the long run.

Author Contributions

All authors participated in ideation, development, and writing the manuscript. All authors read and approved the final manuscript.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this article.



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Informed Consent

Not applicable. This study did not involve human participants requiring informed consent. The data used in this research were obtained from anonymized financial records with all personally identifiable information removed. No private or sensitive information was collected from individuals.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request. Due to privacy and confidentiality considerations, raw financial data may not be publicly distributed but can be accessed through the corresponding author with appropriate data use agreements and institutional approvals. The authors are committed to transparency and will provide detailed methodological information, model specifications, and analysis protocols upon request.

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