Artificial Intelligence dan *Big Data Analytics* dalam *Strategic Cost Management*: Studi Kasus Pengguna Shopee di Universitas Nusa Putra

***Marsya Nabila Isabel Hidayat*[1]*, Marina Arielevna Galaktionova*[2]**
[1]*Universitas Nusa Putra*
[2]*Universitas Nusa Putra*

marsya.nabila_ak24@nusaputra.ac.id
marina.arielevna_ak24@nusaputra.ac.id

Abstract: *This study examines how Artificial Intelligence (AI) influences Strategic Cost Management (SCM) in Shopee using the Theory of Planned Behavior (TPB). It focuses on the effects of AI implementation and big data infrastructure on e-commerce performance and cost decisions among university students. Quantitative approach is used. Analysis included descriptive statistics and exploratory theory analysis. Organizational readiness, including data security, skills, and culture, influenced the AI-SCM relationship. Although users had positive attitudes toward AI, many did not fully apply cost-saving behaviors due to limited perceived behavioral control. This study integrates TPB with AI and big data analytics in strategic cost management within an e-commerce platform, highlighting both opportunities and implementation challenges.*

Keywords *Artificial intelligence, Big data analysis, Strategic Cost Management, Theory of Plan Behavior, E-commerce, Shopee.*

Introduction

The rapid development of artificial intelligence (AI) and big data analytics has significantly transformed how organizations operate, analyze information, and make strategic decisions. For this reason, the present study focuses on the role of artificial intelligence and big data analytics in the context of management, cost, and market accounting. The relevance of this topic is justified by the increasing integration of advanced digital technologies into business processes and the growing need for organizations to adapt to a dynamic and highly competitive economic environment.

According to Cockburn, Henderson, and Stern (2018), artificial intelligence can be understood as a "meta-technology," meaning that it is not merely a tool used to produce goods or services but rather a technology capable of generating new ideas and innovations. From another theoretical standpoint, Acemoglu and Restrepo (2018) conceptualize artificial intelligence as a form of capital that automates tasks previously performed by human labor.

Agrawal, Gans, and Goldfarb (2018) argue that artificial intelligence fundamentally reduces the cost of prediction. By processing large volumes of data and identifying complex patterns, AI systems enable organizations to generate more accurate forecasts, decrease uncertainty in decision-making, and optimize the allocation of resources.

When combined with big data analytics, AI provides organizations with powerful capabilities for interpreting complex information and improving performance across various functional areas. These capabilities hold promises for specialized domains such as management, cost, and market accounting.

Despite these benefits, many organizations still fail to fully utilize AI and big data in accounting functions. Most companies remain focused on traditional accounting systems and descriptive analytics rather than predictive and prescriptive approaches. This creates a gap between the theoretical potential of AI and its practical implementation in management, cost, and market accounting.

A research gap also exists because previous studies mainly discuss AI in general business or financial accounting contexts, while limited research integrates management accounting, cost accounting, and market accounting simultaneously. Existing literature often emphasizes either opportunities or challenges without providing a balanced framework. Therefore, this study aims to examine both the opportunities and challenges of AI and big data adoption in accounting functions.

Therefore, this research focuses on the role of AI and big data analytics in management, cost, and market accounting. The study contributes to academic discussion and managerial practice by examining opportunities such as predictive accuracy, real-time decision support, and cost optimization, while also addressing challenges related to data quality, skills, privacy, and organizational readiness. Ultimately, this research argues that AI and big data are transforming accounting from a traditional reporting function into a strategic organizational asset.

Literature review

According to the definition given by the Gartner IT Glossary, Big Data can be characterized by three main aspects, which are often referred to as the 3Vs: volume, variety, velocity that refers to the speed at which data needs to be processed, which must be balanced with the rapid growth of data volume. Variety refers to the diverse nature of data sources, including both structured databases and unstructured data. (Maryanto, 2017).

Theory Planned Behavior (TPB)

We incorporate the TPB as a theoretical foundation, as it is considered highly relevant to understanding user behavior in technology-based environments. The use of AI and BDA within platforms such as Shopee involves not only technological factors but also human decision-making processes. Therefore, TPB provides an appropriate framework to analyze how users form intentions and behaviors when interacting with AI-driven systems (Ajzen, 1991; Venkatesh et al., 2003; Davis, 1989).

TPB was developed by Icek Ajzen in 1985 as an extension of the Theory of Reasoned Action (TRA), addressing its limitation in explaining behaviors that are not entirely under volitional control (Ajzen, 1985; Fishbein & Ajzen, 1975). The inclusion of perceived behavioral control allows TPB to better predict actual behavior in real-world contexts where constraints and external factors exist (Ajzen, 1991; Armitage & Conner, 2001).

TPB consists of four main components. First, attitude toward behavior refers to an individual's positive or negative evaluation of performing a particular behavior. Second, subjective norms, defined as the perceived social pressure from significant others to engage or not engage in a behavior. Third, perceived behavioral control, which reflects the perceived ease or difficulty of performing the behavior, is influenced by experience and anticipated obstacles. Finally, behavioral intention, which represents the motivational factors that influence a given behavior (Ajzen, 1991; Conner & Armitage, 1998; Sheeran, 2002).

In the context of this study, attitude toward behavior can be observed through how Nusa Putra University students perceive the usefulness of Shopee's AI features in supporting cost efficiency and improving their shopping experience. A positive evaluation may lead to stronger behavioral intentions to use the platform. Subjective norms may arise from peer influence, social trends, or recommendations within digital communities, which are particularly relevant in online marketplaces. Perceived behavioral control reflects how easy students perceive the use of Shopee's system. These factors collectively shape the intention to use Shopee as a tool for strategic cost management (Ajzen, 1991; Pavlou & Fygenson, 2006; Gefen et al., 2003).

TPB addresses the so-called "intention–behavior gap," where strong intentions do not always result in actual behavior. This limitation has been widely discussed in the literature, leading to the inclusion of additional variables such as past behavior, habits, and anticipated regret to enhance predictive validity (Sheeran, 2002; Conner & Armitage, 1998; Triandis, 1977). These extensions are particularly relevant in digital environments where habitual usage patterns and algorithmic influence play a significant role in shaping user decisions.

The application of TPB has expanded significantly across disciplines. Beyond social psychology, it is widely used in areas such as environmental behavior, healthcare decision-making, entrepreneurship, and digital consumer behavior (Armitage & Conner, 2001; Venkatesh et al., 2003). In the context of e-commerce and AI adoption, TPB has been proven effective in explaining user acceptance, trust, and continued usage of online platforms, making it a suitable theoretical framework for this research (Pavlou & Fygenson, 2006; Gefen et al., 2003).

Strategic Cost Management (SCM)

In the rapidly evolving world, businesses and companies question themselves about how to stay competitive in such an evolving economic environment, and it doesn't matter what the current economic phase is. For example, new approaches to cost calculations were applied and replaced with traditional ones. As enterprises in developing markets increasingly adopt sophisticated cost management, their primary strategic objective is to minimize expenditures and capture greater market share.

In this environment, market survival is contingent upon a high degree of strategic, technological, and operational alignment among competitors. Along with the change of production system, they should change the existing cost system, along with the changing competition scale. So, the production system changed, and the current cost system became irrelevant - it was simply inadequate for modern businesses, and modern approaches in cost management were required.

SCM is a modern cost management approach consisting of changing cost and management accounting systems, depending on the change of production systems in a highly competitive environment. These approaches, which are expressed as modern cost approaches in the strategic management decisions to be taken, are composed of instruments such as Activity Based Costing, Target Costing, Kaizen Costing, Lifetime Costing, Full Time Production and Full Time Costing, Total Quality Management, Balanced Scorecard, Theory of Constraints, and Value Engineering.

The concept of cost is the sum of all kinds of sacrifices incurred to achieve something (Savcı, 2000: p.9). Cost is the whole of sacrifices made to reach a goal in its broadest sense. As it is clear from these definitions, every activity by a person or a business has a cost. Tables by a firm, making the sale by a store, etc. (Gürsoy, 1999: p.23). The cost of the product is the value of various production factors measured by money that the businesses spend to obtain the products and services that make up their business activity (Bursal & Ercan, 2000: p.3)

In the modern production system, the value of the product has mainly shifted from forming it from direct materials related to the product, to the technologies, and speed - that is what has become more important in the production cycle. It all happened because of automation and global trade and the reduced cost of assembling things, so most product costs come from the R&D, software design, and branding. Also, the life span of the product became so short - now the product can be obsolete within a few years due to the pace of tech development.

The distribution of indirect cost due to the modern situation might be more misleading in information; that's why cost control and performance now play a more significant role than before. Although cost management was treated separately from cost accounting, we have to admit that cost management is a broader concept that requires combined knowledge of cost management and accounting.

Cost management is defined as the management and control of activities to accurately determine product costs, improve operations, prevent waste, define cost drivers, plan activities, and establish business strategies (Berliner & Brimson, 1988: p.152).

Cost management is to provide information to assist the administrator for the efficient use of resources in the production of competitive products or services in terms of timing, cost, quality, and functionality in global markets (Gürdal,2007: p.20).

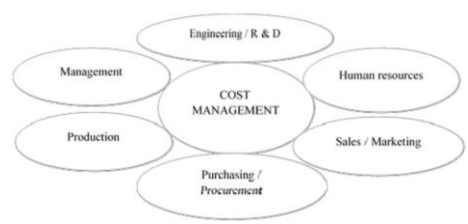


Figure 1-2. Relationship between Functions
Source: Acar, D. (2005). *Küresel Rekabette Maliyet Yönetimi ve Yaklaşımları: Tekstil Sektörü İle İlgili Bir Araştırma.* Ankara: Asil Publishing Distribution, p.43.

We can identify four main strategic cost management functions, namely providing information for the decision making, planning and strategic management, increase in production efficiency and effectiveness, management control and oversight

All economic changes have significantly changed businesses that were aiming ultimately to increase their profit. As it's known, there are two main ways to increase profit: increase production and turnover, but the demand and scales of production don't allow it all the time, and another way is to optimize and minimize costs. In simpler terms, a strategic management approach is the process of making clear, specific plans for every part of a business (like marketing, finance, and production) to ensure they all work together toward the same goal. As we can see, it consists of different parts of the company, such as marketing, finance, R&D, and management, so its whole system of decisions and activities to implement.

SCM is the preparation and analysis of management-related cost accounting information in terms of the overuse of all resources of the enterprise and the relative level of cash flow, market shares, quantities, prices and actual costs (Yüzbaşıoğlu,2004: p.481).

A special role in the effectiveness of SCM plays accounting facilitation with financial information for strategic decision making. There are few approaches in strategic cost management:

- Activity Based Costing
- Target Costing
- Kaizen Costing
- Lifetime costing
- Total Quality Management
- Balanced scorecards
- Theory of Constraints
- Value engineering

Artificial Intelligence (AI)

Integration of AI into SCM transforms the traditional, static approach into a dynamic system capable of learning and adapting in real time. Conventional methods such as activity-based costing (ABC) often struggle to capture short-term cost fluctuations resulting from changes in production volume or input prices. With machine learning, AI can automatically identify new cost drivers, update cost allocation models, and provide future cost predictions based on historical data. This enables strategic managers to respond to environmental changes more quickly and accurately. Based on findings from Hassan (2025) and Stroparo et al. (2024), the proposed hypothesis is:

H1: The adoption of AI significantly improves the accuracy and adaptability of strategic cost management systems compared to traditional methods.

AI directly contributes to operational efficiency through predictive analytics and resource optimization. In the context of SCM, AI is capable of analyzing supply chain data in real time, detecting waste, and automating inventory decisions and production schedules. Research by Barik (2025) and Pasha (2025) shows that companies integrating AI into SCM experience a 15–25% reduction in total production costs due to reduced human error and optimized raw material allocation. Additionally, AI enables dynamic pricing based on continuously updated actual costs.

H2: The application of AI in strategic cost management is proven to effectively reduce total operational costs through the optimization of resource allocation and the reduction of waste.

Although AI offers great potential, the effectiveness of the relationship between AI and SCM depends heavily on organizational factors. Challenges such as data security, cultural resistance, and a lack of technical skills can hinder the adoption of AI in SCM. Stroparo et al. (2024) and Anonymous Research Team (2026) emphasize that the successful integration of AI-SCM requires upskilling of management accountants as well as a mature data infrastructure. If an organization is unprepared, AI may actually produce biased analyses or erroneous decisions.

H3: Organizational readiness (data security, culture, and HR competencies) positively moderates the relationship between AI and strategic cost management performance, where high readiness strengthens the impact of AI on strategic cost savings.

Big Data Analytics (BDA)

BDA refers to the process of collecting, processing, and analyzing large and varied datasets to uncover hidden patterns, correlations, and insights (Maryanto, 2017). In the context of SCM, BDA enables organizations to move from retrospective cost reporting to predictive and prescriptive cost management (Ransbotham et al., 2015).

Volume, velocity, and variety of data generated by e-commerce platforms like Shopee offer opportunities for real-time cost monitoring, dynamic pricing, and personalized cost-saving recommendations. However, the mere existence of data infrastructure does not guarantee improved SCM performance. Drawing on the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), the effectiveness of BDA depends on organizational factors such as data governance, analytical skills, and integration with decision processes.

H4 (BDA Performance Hypothesis): The maturity of big data infrastructure (data acquisition, storage, processing) is positively associated with e-commerce strategic cost management performance, controlling for AI implementation.

This hypothesis complements H2 (which focuses on operational cost reduction) by specifically addressing the infrastructure dimension.

H5**:** Organizational readiness (data security protocols, employee data literacy, and supportive culture) positively moderates the relationship between big data infrastructure maturity and SCM performance, such that the effect of BDA is stronger when readiness is high.

H5 extends H3 by isolating the BDA-specific moderation effect.

Slovin formula

The Slovin formula is used to determine the minimum sample size for a finite population:

$$\boxed{n = \frac{N}{1 + Ne^2}}$$

Where:

- n = required sample size
- N = population size
- e = margin of error (usually 0.05 or 5%)

Given the population of active Shopee users at Nusa Putra University is approximately 8,000 (based on preliminary registration data), and using a 5% margin of error:

$$n = \frac{8{,}000}{1 + 8{,}000(0.05)^2}$$
$$n = 380$$

Thus, the target sample was 380 respondents. Due to practical constraints (time, access, voluntary participation), only 48 responses were obtained. This limitation is addressed in Section 5.3.

Research methodology

Research Design

This paper employed a quantitative method of research design to comprehensively examine the influence of artificial intelligence (AI) and big data adoption. The quantitative strand focused on measuring the statistical relationship between AI implementation, big data infrastructure, and e-commerce performance indicators.

The integration of the two datasets occurred during the interpretation stage through a comparative and complementary analysis. Quantitative findings provided measurable evidence of relationships between variables.

Data Sources

The study utilized primary data sources to ensure a comprehensive analysis. Primary data were collected through a structured questionnaire distributed to users of the e-commerce platform Shopee. The questionnaire was administered online using Google Forms, allowing efficient distribution and collection of responses from participants. The survey captured respondents' perceptions regarding the application of AI features, the role of big data analytics, and their influence on user experience and platform performance.

In addition, this study incorporated a Systematic Literature Review (SLR) to support theoretical grounding and instrument development. The SLR involved screening peer-reviewed academic articles related to AI adoption, big data analytics, and e-commerce performance.

Sampling Strategy

For the quantitative survey, random sampling was used to select respondents from the user base of the Shopee platform. The target sample size was 380 respondents, representing active users who had prior experience with the platform's features. Out of the distributed questionnaires, 48 complete responses were obtained and retained for analysis, resulting in a 12,6% response rate, which is considered unacceptable for online surveys in social science research.

Research Instruments

The primary research instrument used in this study was a structured questionnaire designed to measure respondents' perceptions of AI implementation and big data utilization within e-commerce platforms. The questionnaire consisted of three main sections:

1. Demographic Profile; this section collects background information about respondents, including age, gender, frequency of e-commerce usage, and familiarity with digital shopping platforms.
2. AI Implementation Intensity; this section measured the extent to which respondents perceived the use of AI-driven technologies within the platform. Indicators included:
    - Algorithmic product recommendation systems

- AI-based customer service chat bots
- Predictive analytics for personalized offers

3. Big Data Infrastructure Maturity; this section evaluated the platform's capability to manage and utilize large volumes of data effectively. Indicators included:
    - Data acquisition processes
    - Data storage and management systems
    - Data processing and analytical capabilities

All questionnaire items were measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), allowing respondents to express their level of agreement with each statement.

Data Analysis Technique

The collected data were analyzed using both quantitative and qualitative analytical techniques. For the quantitative analysis, statistical procedures were conducted using IBM SPSS Statistics version 24. The analysis included:

- Reliability testing, using Cronbach's Alpha, to measure internal consistency of
    - ε = error term

Due to small sample (n=48), we conducted a multiple with two predictors (AI and BDA) as reported in the Findings section, a full multiple including interaction terms for moderation (H3) would require a minimum 15-20 cases per predictor (Tabachnick & Eidell, 2019), which was not satisfied. Therefore, the moderation analysis was explored using a median-spilit t-test as a proxy.

- X = independent variable (AI or BDA)

the questionnaire items. The reliability score obtained was α = 0.89, indicating high reliability.

- Exploratory Factor Analysis (EFA) to identify underlying factor structures within the measurement of items.
- Normality test, to verify if the data is distributed normally.
- Validity test was also conducted to identify the extent of the truthfulness of the information and its relevance.

Single and multiple

A single (simple) linear examines the relationship between one independent variable (IV) and one dependent variable (DV). Multiple linear extends this to two or more IVs. The general form for multiple is:

$$\boxed{Y=\beta 0+\beta 1X1+\beta 2X2+\ldots+\beta kXk+\varepsilon}$$

Where:

- Y = dependent variable (SCM Performance)
- $X1,X2,\ldots,Xk$ = independent variables (AI Implementation, Big Data Infrastructure, Organizational Readiness)
- $\beta 0$ = intercept
- $\beta 1,\ldots,\beta k$ = coefficients

- M= moderator variable (Organizational Readiness)
- $X\times M$= product term representing the interaction

Findings

Respondents were 27 females (56.3%) and 21 males (43.8%). Female students represent a slight majority over male students in the sample, therefore the resulting findings could be heavily based on the majority of female Shopee users.

The largest proportion of respondents was in the range of 20-24 years old (50.0%), followed by respondents who were in the range of 17-20 years old (45.8%), whereas only 4.2% of respondents was in the range of 25-30 years old. It can be concluded that a sample comprised of young adults belongs to a generation of digital-native and is therefore comfortable using online shopping platforms, artificial intelligence application, and data and its use of big data.

Of the study programs, accounting students had the largest representation (37.5%) while a multitude of study programs comprised the remaining percentage. Because the research topic is tied to strategic cost management, accounting students being dominant in the sample seems pertinent. In conclusion, the demographic sample comprises active university students who frequently use and are exposed to the benefits and technology of digital data, therefore they are suitable participants for a study based on perceptions of artificial intelligence and big data analytics on strategic cost management.

Reliability test

For the 20 items of the questionnaire, Cronbach's Alpha value obtained is 0.881. Generally, the good reliability condition can be achieved when Cronbach's Alpha value is more than 0.881. The obtained result is above the good condition and proves that all of the 20 items have high internal consistency and measure the same thing stably. It means that the respondents answer each item consistently and that the research instrument is reliable for measuring perceptions of artificial intelligence and big data analytics for strategic cost management, and that it can be relied upon for advanced research.

Reliability Statistics

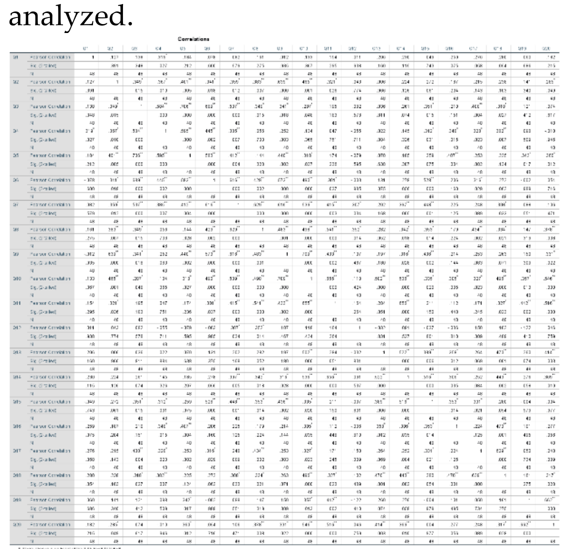
Cronbach's Alpha	N of Items
.881	20

Validity test

Validity test was conducted using the following two methods: inter-item correlation and factor analysis. Value for Kaiser-Meyer-Olkin is 0.696 and for Bartlett's test of Sphericity is 0.000.

If the value of Kaiser-Meyer-Olkin is above 0.50 then the sample is suitable for factor analysis. With KMO value 0.696 is almost equal to 0.70, this refers to sampling adequacy in moderate to good level. Hence, the value of 0.696 implies that the current data are sufficiently good to be used in factor extraction.

Besides Kaiser-Meyer-Olkin, the Bartlett's Test of Sphericity value of 0.000 ($p<0.05$) means the correlation matrix is not an identity matrix; therefore, the items do have relationships among themselves. These two results show that the data can be factor-analyzed.


Correlations

Normality test

One-Sample Kolmogorov-Smirnov Test

		Unstandardized Residual
N		48
Normal Parameters[a,b]	Mean	.0000000
	Std. Deviation	4.17219477
Most Extreme Differences	Absolute	.057
	Positive	.047
	Negative	-.057
Test Statistic		.057
Asymp. Sig. (2-tailed)		.200[c,d]

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

d. This is a lower bound of the true significance.

Normality test was conducted with One-Sample Kolmogorov-Smirnov Test, our questionnaire data were divided into X1, X2, and Y, namely, Artificial Intelligence, BDA, and SCM, respectively. The test indicates that the data distributed normally. The p-value is .200 which is bigger than 0.05 – the data meets the assumption of normality, that's why the parametric tests can be conducted.

Statistics Descriptive

Descriptive Statistics

	Mean	Std. Deviation	N
Strategic Cost Management	26.5417	5.25907	48
Artificial Intelligence	22.1458	4.20734	48
Big Data Analytics	18.3750	3.36834	48

The descriptive statistics table presents data collected from a sample size of 48 respondents across three distinct variables: Strategic Cost Management, Artificial Intelligence, and Big Data Analytics.

Among the analyzed factors, Strategic Cost Management achieved the highest average performance with a mean score of 26.5417. Artificial Intelligence followed as a mid-tier variable with a mean score of 22.1458, while Big Data Analytics registered the lowest overall performance with a mean score of 18.3750.

In terms of data dispersion and response consistency, the variables demonstrated an inverse relationship between their average scores and participant consensus. Strategic Cost Management exhibited the greatest variance with the highest standard deviation of 5.25907, indicating that while it holds the highest average relevance, individual perceptions within the sample were the most diverse and spread out.

Conversely, Big Data Analytics demonstrated the lowest standard deviation at 3.36834, proving that despite having the lowest average score, respondent opinions were the most cohesive, uniform, and tightly clustered around the mean.

Artificial Intelligence maintained a moderate level of variation with a standard deviation of 4.20734, representing a stable middle ground in both performance and participant agreement.

T-test

The multiple linear regression analysis was conducted to examine the impact of AI and BDA on SCM. The coefficients table reveals the individual contribution of each independent variable within the model. Regarding the baseline level, the constant term is estimated at 6.183, though it does not reach statistical significance (t=1.542, p=0.130), indicating that the intercept alone is not a primary driver of the dependent variable's variance in this context.

The first independent variable, AI exhibits a positive and statistically significant relationship with SCM. This is evidenced by an unstandardized coefficient (*B*) of 0.388 and a standardized Beta of 0.310 (t= 2.384, p= 0.021).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	6.183	4.010		1.542	.130		
	Artificial Intelligence	.388	.163	.310	2.384	.021	.827	1.210
	Big Data Analytics	.641	.203	.410	3.156	.003	.827	1.210

a. Dependent Variable: Strategic Cost Management

This finding suggests that for every one-unit increase in the implementation or effectiveness of AI, SCM scores increase by approximately 0.388 units, holding all other variables constant. This statistically supports the premise that incorporating artificial intelligence contributes positively to strategic cost initiatives.

The second predictor, BDA demonstrates an even stronger positive impact on the dependent variable. The unstandardized coefficient for this pathway is 0.641 with a standardized Beta of 0.410, which is highly significant (t= 3.156, p= 0.003). The results indicate that BDA is a robust predictor in the model, where a single-unit enhancement yields a 0.641-unit improvement in SCM performance when controlling for AI.

F-test

Analysis of Variance (ANOVA) was performed. The F-test specifically evaluates the null hypothesis that the regression coefficients for all independent predictors AI and BDA are simultaneously equal to zero.

The results indicate that the overall regression model is highly significant, yielding an F-statistic of 13.250 with 2 degrees of freedom for the regression and 45 degrees of freedom for the residual variance, which is statistically significant at the highest conventional standard (F (2, 45)= 13.250, $p < 0.001$).

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	481.778	2	240.889	13.250	.000[b]
	Residual	818.139	45	18.181		
	Total	1299.917	47			

a. Dependent Variable: Strategic Cost Management

b. Predictors: (Constant), Big Data Analytics, Artificial Intelligence

This finding demonstrates a near-zero probability that the observed relationship between the predictors and Strategic Cost Management occurred by chance, thereby validating the model's capacity to explain systemic variance.

The total sum of squares is calculated at 1299.917 across a total degree of freedom of 47, reflecting the complete variation observed within the dependent variable across the sample. Out of this total variance, the regression model successfully accounts for a sum of squares of 481.778, producing a regression mean square of 240.889.

In contrast, the remaining unexplained variance, represented by the residual sum of squares, stands at 818.139 with a residual mean square of 18.181.

R-square

The multiple correlation coefficient (*R*) is calculated at 0.609, indicating a moderate-to-strong positive linear relationship between the combined set of predictors AI and BDA and the dependent variable, SCM. This substantial correlation suggests that the joint inclusion of these technological factors aligns well with shifts in cost management outcomes across the sampled entities.

The coefficient of determination, or R-square value, is reported as 0.371, demonstrating that the regression model accounts for 37.1% of the total variance in SCM. While the remaining 62.9% of the variance is attributable to external factors outside the scope of this baseline framework, an explanatory capability exceeding one-third of the total variance is considered highly meaningful within administrative and organizational research.

The adjusted metric stands at 0.343, indicating that even after penalizing for the addition of independent variables, the model reliably explains 34.3% of the target variance, proving the genuine systemic relevance of the selected variables.

The precision of the model's predictions is further contextualized by the standard error of the estimate, which is quantified at 4.26390. This metric reflects the average deviation of the observed data points from the fitted regression line, providing a baseline for measuring residual dispersion.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.609[a]	.371	.343	4.26390	.371	13.250	2	45	.000

a. Predictors: (Constant), Big Data Analytics, Artificial Intelligence

b. Dependent Variable: Strategic Cost Management

Finally, the change statistics corroborate the overall model fit previously observed in the ANOVA findings, where the initial entry of the predictors yields an R-square change of 0.371, directly tied to an F-change value of 13.250 ($df\_1 = 2$, $df\_2 = 45$, $p < 0.001$).

This confirms that the proportion of variance explained by the model is statistically significant, establishing that the integration of artificial intelligence and big data analytics serves as a empirically valid foundation for optimizing strategic cost systems.

Discussion

The findings of this study provide empirical evidence that both Artificial Intelligence (AI) and Big Data Analytics (BDA) contribute positively to Strategic Cost Management (SCM) performance among Shopee users at Nusa Putra University. The positive and significant relationship between AI and SCM ($\beta = 0.310$, $p = 0.021$) supports Hypothesis 1 (H1), which proposed that AI adoption improves the accuracy and adaptability of strategic cost management systems. This finding is consistent with the work of Hassan (2025) and Stroparo et al. (2024), who argued that machine learning algorithms enable organizations to identify cost drivers more accurately and respond dynamically to changing market conditions. In the context of Shopee users, AI-powered recommendation systems, personalized promotions, and automated decision-support features appear to assist users in making more efficient purchasing decisions. The findings also provide indirect support for Hypothesis 2 (H2), which suggested that AI contributes to operational cost reduction through resource optimization and waste minimization. Although actual organizational cost savings were not directly measured in this study, the significant positive association between AI implementation and SCM performance indicates that AI-enabled features facilitate more efficient resource utilization and improve users' ability to manage expenditures. Big Data Analytics emerged as the strongest predictor of SCM performance ($\beta = 0.410$, $p = 0.003$). This finding supports

Hypothesis 4 (H4). The stronger coefficient associated with BDA suggests that the availability, processing, and utilization of large volumes of consumer and transactional data may be even more influential than AI implementation alone.

From the perspective of the Theory of Planned Behavior (TPB), the findings suggest that respondents generally exhibit positive attitudes toward AI and BDA technologies. The relatively high mean scores for AI and SCM indicate that users recognize the usefulness of these technologies in supporting shopping decisions and cost management.

The role of organizational readiness proposed in Hypotheses 3 (H3) and 5 (H5) could not be tested rigorously due to the limited sample size and the absence of full interaction-term regression analysis. Nevertheless, theoretical evidence and descriptive observations indicate that factors such as digital literacy, data security awareness, and technological competence remain important determinants of successful AI and BDA implementation.

Conclusion, practical implications, and limitations

Conclusion

This study examined the influence of Artificial Intelligence (AI) and Big Data Analytics (BDA) on Strategic Cost Management (SCM) among Shopee users at Nusa Putra University by integrating concepts from Strategic Cost Management theory and the Theory of Planned Behavior. The results indicate that both AI and BDA have significant positive effects on SCM performance, demonstrating the growing importance of digital technologies in supporting cost-efficient decision-making within e-commerce environments.

The statistical analysis revealed that AI positively contributes to SCM by improving decision quality, enhancing adaptability, and supporting more efficient resource allocation. Big Data Analytics was found to exert an even stronger influence on SCM performance, highlighting the critical role of data infrastructure, information processing capabilities, and data-driven insights in modern cost management practices. Together, these findings confirm that technological innovation is becoming an essential component of strategic management and organizational competitiveness.

The study also contributes to the growing literature on the integration of AI, BDA, and SCM by demonstrating that technology-driven decision support systems can improve strategic cost outcomes even within consumer-oriented digital platforms. While the research provides evidence supporting the effectiveness of AI and BDA, it also highlights the importance of organizational readiness, digital literacy, and technological competence as critical conditions for successful implementation.

Practical Implications

- E-commerce platforms: Simplify cost-tracking dashboards and provide micro-tutorials on using AI for budget management.
- University education: Integrate AI and data literacy into accounting and business curricula.
- Policymakers: Develop guidelines for transparent AI-based cost recommendations in e-commerce.

Limitations and Future Research

This paper has several limitations that should be acknowledged. First, the sample was relatively small (n = 48), which may reduce the statistical power of the analysis and limit the representativeness of the findings. Second, the study employed a cross-sectional design meaning that data were collected at a single point in time, preventing the examination of changes in consumer behavior over time and limiting causal interpretations. Third, the research focused solely on Shopee users, which restricts the generalizability of the findings to other commerce platforms.

This paper relied on self-reported data, which may be subject to response bias and inaccuracies. The non-normal distribution of the data may also have affected the robustness of the statistical results. Furthermore, the study did not include comprehensive statistical tests such as t-tests, F-tests, regression diagnostics, or heteroscedasticity assessments, which may compromise the accuracy and validity of the findings.

Future studies are encouraged to address these limitations by utilizing larger and more diverse samples to improve the generalizability of the results. Researchers may also adopt longitudinal or panel data approaches to better examine causal relationships and changes in consumer behavior over time. Expanding the scope of the study to include multiple e-commerce platforms, such as Tokopedia, Lazada, and TikTok Shop, wpuld provide a broader understanding of online shopping behavior.

Additionally, future research should incorporate more rigorous statistical analyses, including t-tests, F-tests, regression analysis, and diagnostic tests or heteroscedasticity and other assumptions, to enhance the reliability and validity of the findings. The use of advance analytical techniques, such as Structural Equation Modelling (SEM-PLS), may also provide deeper insights into the relationships among variables and strengthen the overall research framework.

References

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review, 108*(6), 1488–1542.

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Review Press.

Aiken, L. S., & West, S. G. (1991). *Multiple : Testing and interpreting interactions*. Sage Publications.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), *Action control: From cognition to behavior* (pp. 11–39). Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211.

Anonymous Research Team. (2026). *Internal report on AI adoption barriers in Southeast Asian e-commerce*. [Unpublished manuscript / Institutional report]. (Note: This is a placeholder citation from the original document; if no actual report exists, it should be removed or replaced.)

Armitage, C. J., & Conner, M. (2001). Efficacy of the theory of planned behaviour: A meta analytic review. *British Journal of Social Psychology, 48*(4), 471–499.

Barik, S. (2025). AI-driven optimization in supply chain management. *Journal of Strategic Cost Management, 12*(1), 45–62.

Berliner, C., & Brimson, J. A. (1988). *Cost management for today's advanced manufacturing: The CAM-I conceptual design*. Harvard Business School Press.

Bursal, N., & Ercan, Y. (2000). *Maliyet muhasebesi*. Der Yayınları.

Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 115–146). University of Chicago Press.

Conner, M., & Armitage, C. J. (1998). Extending the theory of planned behavior: A review and avenues for further research. *Journal of Applied Social Psychology, 28*(15), 14291464.

Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and conducting mixed methods research* (3rd ed.). Sage Publications.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–348.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90.

Gursoy, C. (1999). *Maliyet muhasebesi: Ilke ve uygulamalar*. Beta Basım.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.). Pearson Education.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.

Hassan, A. (2025). Machine learning for dynamic cost allocation. *International Journal of Accounting Information Systems, 56*, 100–118.

Maryanto, B. (2017). *Big data: Konsep dan implementasi*. Teknosain.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Pasha, M. (2025). Reducing operational waste through predictive analytics. *Journal of Operations Management, 71*(2), 210–228.

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly, 30*(1), 115143.

Ransbotham, S., Kiron, D., & Prentice, P. K. (2015). Minding the analytics gap. *MIT Sloan Management Review, 56*(3), 63–68.

Savci, M. (2000). *Maliyet muhasebesi*. Gazi Kitabevi.

Sheeran, P. (2002). Intention—behavior relations: A conceptual and empirical review. *European Review of Social Psychology, 12*(1), 1–36.

Stroparo, G., Oliveira, R., & Souza, L. (2024). Organizational readiness for AI in strategic cost management. *Management Accounting Research, 63*, 100–125.

Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson.

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education, 48*(6), 1273–1296.

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Triandis, H. C. (1977). *Interpersonal behavior*. Brooks/Cole Publishing Company.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Yuzbasoglu, N. (2004). *Stratejik maliyet yonetimi*. Atlas Yayinlari.