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Impact of supply chain cost management practices on competitive advantage: Evidence from the Indian automobile industry

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Abstract
This study examines how strategic supply chain cost management practices (SCCMP) influence the competitive advantage (CA) of Indian automobile companies. Utilizing a descriptive, cross-sectional survey design, data were collected from 49 companies affiliated with the Society of Indian Automobile Manufacturers (SIAM). Exploratory and confirmatory factor analyses validated the constructs, while Partial Least Squares Structural Equation Modelling (PLS-SEM) tested the hypothesized relationships. Results show that practices such as Target Costing, Activity-Based Costing, Kaizen Costing, and Open Book Accounting significantly enhance firms' abilities to compete on price, quality, delivery dependability, innovation, and time to market. The structural model demonstrated strong explanatory power ($R^2 = 0.896$), large effect size ($f^2 = 0.469$), and excellent out-of-sample predictive accuracy. The findings underscore the strategic value of cost-focused supply chain initiatives, offering critical insights for both academia and practitioners in emerging economies.

Keyword: Strategic cost management, supply chain, competitive advantage, PLS-SEM, Indian automobile industry

Introduction

In recent decades, the strategic role of supply chain management (SCM) in enhancing firm performance and competitiveness has been widely recognized (Johnson & Lawrence, 1988; Harland, 1996; Margretta, 1998; Chandra & Kumar, 2000; Bagchi & Skjoett-Larsen, 2002) [46, 41, 56, 16, 7]. Simultaneously, a parallel body of literature has highlighted the importance of strategic cost management (SCMgt) tools in improving supply chain efficiency (Bromwich & Bhimani, 1989; Shank, 1989; Shank & Govindarajan, 1993; Cooper & Slagmulder, 1998; Seuring, 2002) [13, 66, 67, 20, 65]. Despite their shared objective of managing and minimizing costs, empirical research that integrates SCMgt tools into broader SCM frameworks has remained limited.

Historically, SCM and SCMgt have developed along separate academic paths. As a result, the accounting literature has largely overlooked their intersection (Hopwood, 1996; Axelsson *et al.*, 2002; Cooper & Slagmulder, 2004) [43, 6, 21]. As Seuring (2002, p. 1) [65] notes, "if costs are to be reduced, companies increasingly turn their attention to their supply chain partners… Yet, few approaches exist so far, addressing how cost management in a supply chain can be carried out." Most existing studies focus narrowly on dyadic firm relationships (Cooper & Yoshikawa, 1994; Dekker, 2003, 2004; Hakansson & Lind, 2004) [22, 27, 40], with limited attention given to cost coordination across complex, multi-firm supply networks (Choi & Hong, 2003; Cooper & Slagmulder, 2004) [19, 21]. This fragmented view falls short of capturing the interconnected and boundary-spanning nature of modern supply chains (Hopwood, 1996). While some empirical work from developed economies has begun to examine inter-organizational cost management (Cullen *et al.*, 1999; Kajüter, 2002; Seuring, 2002; Goldbach, 2002; Slagmulder, 2002; Rebitzer, 2002) [64, 47, 65, 70, 60], research in emerging economies particularly India remains scarce. In India, most studies focus on general SCM practices and their relationship with firm performance (Suhong Li *et al.*, 2006; Thatte *et al.*, 2013) [72, 73], without specifically investigating the role of cost management tools within these supply chains. In light of this gap, the present study explores how Indian automobile companies employ strategic cost management techniques within their supply chains and how these practices influence competitive advantage. It seeks to answer the following research questions:

1. To what extent are cost management techniques integrated across supply chains in Indian automobile companies?
2. What is the impact of these cost management practices on the competitive advantage of these firms?

This study contributes to the literature by offering empirical insights at the intersection of SCM and SCMgt, particularly within the under-researched context of developing economies. The findings are expected to inform both academic understanding and managerial practices, offering a foundation for future inquiry into inter-organizational cost management in dynamic supply chain environments. The study is structured to provide a coherent flow from theory to findings. Section 2 reviews key literature on supply chain management and cost management techniques. Section 3 explains the research methodology, while Section 4 presents the study's findings. These results are analysed in depth in Section 5, followed by a comparative discussion in Section 6 with similar studies. The research concludes in Section 7, highlighting key implications for future research on cost management within Indian supply chains.

Historical Background of Cost Economics and Strategic Cost Management in Supply Chains

Over the past few decades, Supply Chain Management (SCM) has transitioned from being viewed merely as an operational support function to a critical strategic lever for enhancing organizational competitiveness. Scholars have increasingly emphasized that SCM, when approached strategically, facilitates agility, responsiveness, and value creation across interconnected firms (Poirier, 1998; Dekker & Van Goor, 2000; Bommer *et al*., 2001; Bagchi & Skjoett-Larsen, 2002) [59, 29, 12, 7]. Through greater collaboration among supply chain partners, firms can jointly optimize performance by reducing inefficiencies and managing costs across the entire value network. Understanding the fundamental principles of SCM is essential to effectively integrate cost management tools within these networks. A strategic view of SCM lays the groundwork for examining how firms can embed cost-focused methodologies to not only drive internal efficiency but also strengthen inter-organizational competitiveness. However, conventional cost accounting systems have often been found inadequate in supporting such strategic coordination. Critiques of traditional management accounting highlight its inward-looking orientation and limited relevance for strategic decision-making (Kaplan, 1984, 1988; Johnson & Kaplan, 1987; Ezzamel *et al*., 1990; Scapens, 1999) [49, 45., 32, 63]. These systems typically focus on cost control within individual firms, failing to account for the complexity and interdependence of modern supply chains. As a result, they are often misaligned with the needs of supply chain-wide decision-making and performance optimization. In response, the concept of Strategic Cost Management (SCMgt) has gained prominence. Unlike traditional cost approaches, SCMgt adopts a proactive, value-driven perspective, focusing on shaping cost structures and behaviours across the entire supply chain (Bromwich & Bhimani, 1989; Shank & Govindarajan, 1989; Cooper & Slagmulder, 1998; Seuring, 2002) [16, 67, 13]. It extends beyond the enterprise boundary and integrates cost analysis with strategic objectives at both the firm and network levels. Strategic cost management encompasses tools and practices such as target costing, activity-based costing (ABC), just-in-time (JIT) systems, and total quality management (TQM) (Lockamy & Smith, 2000; Goldbach, 2002; Blocher *et al*., 2002) [52, 37, 11]. These methodologies are designed not only to control and reduce costs but also to align operations with customer value expectations and long-term strategic goals. For instance, target costing facilitates design-to-cost practices; ABC helps identify and manage cost drivers; JIT reduces inventory and waste; and TQM enhances quality while minimizing cost variability. However, the successful deployment of strategic cost management tools requires more than technical competence it depends on a set of enabling conditions that foster inter-organizational cooperation. Key enablers include top management support (Agrawal & Mehra, 1998) [1], open-book accounting (Cullen *et al*., 1999; Seal *et al*., 1999) [64], inter-company teams, mutual trust, and fair sharing of costs and benefits (Dekker, 2003) [20]. These mechanisms create transparency and facilitate collaborative planning and cost control. Moreover, value and profit-sharing mechanisms reinforce the cooperative orientation of supply chain cost management. When firms approach cost control as a shared, system-level objective rather than a zero-sum negotiation, it promotes equitable outcomes and sustainable relationships (Chivaka, 2015) [18]. Such relational governance fosters trust and ensures that cost savings translate into long-term competitive advantage for all parties involved.

Empirical studies reinforce the effectiveness of these tools and enablers. Kajüter (2002) [47], for example, documented the use of target costing in the automotive industry, where a unified Target Achievement Plan enabled multi-tier suppliers to jointly analyse and reduce costs. Seuring (2002) [65] applied similar logic to the apparel sector, demonstrating the role of collaboration in managing both direct and transaction costs. Goldbach (2002) [37] and Slagmulder (2002) [70] highlighted the importance of ABC in tracing internal and inter-firm cost drivers, thereby enhancing transparency and accountability.

In addition, Cooper and Slagmulder (2004) [20] illustrated how target costing can integrate customer needs, design requirements, and supplier capabilities in Japanese supply chains. Rebitzer (2002) [60] introduced life-cycle costing (LCC) in industries such as automotive and aerospace, balancing economic feasibility with environmental impacts and long-term sustainability. Open-book accounting, as explored by Cullen *et al*. (1999) [64] and Seal *et al*. (1999) [64], further reinforces joint commitment to transparency, cost efficiency, and shared performance. Taken together, these contributions highlight that strategic cost management, when embedded within SCM frameworks, plays a vital role in enhancing both operational performance and strategic alignment. By promoting trust, transparency, and mutual gain, these practices enable firms to move beyond traditional cost-cutting measures and toward sustainable, value-driven supply chain collaboration.

Research Objective

Based on the identified gaps, the study sets out the core objective as:

To analyse how supply chain cost management practices influence competitive advantage.

Research Methodology

This study adopts a quantitative, descriptive, and cross-sectional research design to examine the relationship between Supply Chain Cost Management Practices (SCCMP) and Competitive Advantage (CA) within the Indian automobile industry. A descriptive framework is well-suited for identifying and explaining associations among variables, while a cross-sectional design provides a timely snapshot of organizational practices and managerial perceptions (Malhotra & Dash, 2016; Cooper *et al*., 2015) [55, 23]. To gather empirical data, a survey-based strategy was employed using a self-administered questionnaire, enabling efficient outreach across a geographically dispersed and professionally diverse respondent base. The instrument utilized a five-point Likert scale to measure perceptions of SCCMP and its influence on CA dimensions, including price, quality, delivery dependability, product innovation, and time to market. The self-completion format minimized interviewer bias and promoted consistency in responses (Kothari, 2004) [51]. The study followed a census approach, targeting all eligible professionals from automobile firms listed in the Society of Indian Automobile Manufacturers (SIAM) directory. A total of 178 questionnaires were distributed through both online and offline channels. Of these, 108 responses were received, and after data cleaning to remove incomplete or inconsistent entries, 97 valid responses were retained yielding a usable response rate of 54.45%, consistent with executive-level research norms (Baruch & Holtom, 2008) [9]. The final sample comprised 37 supply chain managers, 30 procurement officers, and 30 cost managers, ensuring balanced representation across relevant functional roles (Table 1).

Table 1: Summary of details of respondents

Category of Respondents	Questionnaires Distributed	Valid Responses Retained
Supply Chain Managers	70	37
Procurement Officers	58	30
Cost Managers	50	30
Total	**178**	**97**

A purposive sampling strategy underpinned respondent selection, focusing on professionals with direct involvement in cost-related supply chain decisions. This approach is especially appropriate when domain-specific expertise is critical to addressing the study's objectives (Patton, 2014; Etikan *et al*., 2016) [31, 38].

Following data collection, responses were screened and processed using SPSS v26 to check for missing values, assess normality, and confirm reliability via Cronbach's alpha. The main statistical analysis was conducted using SmartPLS v4, leveraging Partial Least Squares Structural Equation Modelling (PLS-SEM). This technique is particularly effective for testing complex models involving latent variables and is well-suited to studies with relatively smaller sample sizes (Hair *et al*., 2017, 2019) [38].

By integrating a robust design, methodical sampling, and rigorous analytical techniques, this study ensures the validity and reliability of its findings and contributes valuable insights into the strategic role of supply chain cost management in fostering competitive advantage within the Indian automobile sector.

Exploratory Factor Analysis (EFA) of Supply Chain Cost Management Practices

To examine the underlying structure of the Supply Chain Cost Management Practices (SCCMP) construct, an Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis (PCA) with Varimax rotation. This analysis aimed to validate the dimensionality and construct validity of the scale.

Prior to extraction, as indicated in Table 2, the suitability of the data was confirmed through Bartlett's Test of Sphericity (χ^2 = 2828.205, p<0.001) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (KMO = 0.875), both indicating that factor analysis was appropriate (Bartlett, 1950; Cerny & Kaiser, 1977) [8, 15].

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.875
Bartlett's Test of Sphericity	Approx. Chi-Square	2828.205
	Df	12
	Sig.	0.000

Four components with eigenvalues ≥ 1 were retained, collectively explaining 65.22% of the total variance—exceeding the commonly accepted 60% threshold (Hooper, 2012). All 20 items demonstrated strong factor loadings > 0.50, and communalities ranged between 0.642 and 0.851, confirming good explanatory power (see Table 3).

The factors were conceptually clear and evenly distributed, each comprising five items, and were labelled as:

- **F1:** Target Costing
- **F2:** Activity-Based Costing
- **F3:** Kaizen Costing
- **F4:** Open Book Accounting

This factor structure is well-defined and offers a robust foundation for further analysis.

Table 3: Summary of Results from Scale Purification: Communalities, Eigen Value and Explained Variance

Factors	Item No	Elements	Communalities	Eigen Value	Explained Variance
Target Costing	**TC1**	Our company sets target costs based on customer expectations and market conditions.	0.643	6.25	53.627
	TC2	Target costing is integrated into our product development process to control costs.	0.745		
	TC3	We collaborate with suppliers to achieve target cost objectives.	0.772		
	TC4	Target costing has led to improved cost efficiency in our supply chain.	0.737		
	TC5	Implementing target costing has enhanced our competitive advantage.	0.700		
Activity Based Costing	**ABC1**	Our organization uses ABC to allocate overhead costs accurately.	0.764	3.89	58.481
	ABC 2	ABC provides insights into the cost drivers of our supply chain activities.	0.777		
	ABC 3	Implementing ABC has improved our pricing and product mix decisions.	0.766		
	ABC 4	ABC has enhanced our ability to identify non-value-adding activities.	0.799		
	ABC 5	The use of ABC has contributed to better cost management across the supply chain.	0.784		
Kaizen Costing Kaizen Costing	**KC1**	Our company employs Kaizen costing for continuous cost reduction during production.	0.851	3.18	61.933
	KC2	Employees are encouraged to suggest cost-saving improvements regularly.	0.788		
	KC3	Kaizen costing has led to incremental improvements in our production processes.	0.753		
	KC4	We track cost reduction achievements resulting from Kaizen initiatives.	0.788		
	KC5	Kaizen costing has positively impacted our operational efficiency.	0.688		
Open Book Accounting Open Book Accounting	**OBA1**	We share relevant cost information with our supply chain partners.	0.679	2.944	56.419
	OBA2	Open book accounting has fostered trust between our company and suppliers.	0.734		
	OBA3	Collaborative cost management through open book accounting has led to mutual benefits.	0.689		
	OBA4	We use shared cost data to identify areas for joint cost reduction.	0.842		
	OBA5	Open book accounting has enhanced transparency in our supply chain operations.	0.732		

Extraction Method: Principal Component Analysis.

Rotated Component Matrix of Supply Chain Cost Management Practices Scale

The rotated component matrix revealed that each of the four extracted factors consisted of five items with strong loadings above 0.50, indicating a high degree of association between the observed variables and their respective components. This clearly reflects the internal consistency and construct validity of the scale used to measure Supply Chain Cost Management Practices (SCCMP). As presented in Table 4, the results confirm that the measurement instrument effectively captures the dimensions it intends to assess.

Table 4: Rotated Component Matrix of Supply Chain Cost Management Practices

Item Code	Target Costing (F1)	Activity Based Costing (F2)	Kaizen Costing (F3)	Open Book Accounting (F4)
TC1	0.643			
TC2	0.745			
TC3	0.772			
TC4	0.737			
TC5	0.700			
ABC1		0.764		
ABC2		0.777		
ABC3		0.766		
ABC4		0.799		
ABC5		0.784		
KC1			0.851	
KC2			0.788	
KC3			0.753	
KC4			0.788	
KC5			0.688	
OBA1				0.679
OBA2				0.734
OBA3				0.689
OBA4				0.842
OBA5				0.732

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization

Exploratory Factor Analysis (EFA) of Competitive Advantage Scale

To uncover the dimensional structure of the Competitive Advantage construct, Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis (PCA) with Varimax rotation. Prior to extraction, data adequacy was assessed using Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity. The KMO value of 0.807 confirms meritorious sampling adequacy (Cerny & Kaiser, 1977) [15], while the significant result of Bartlett's Test (χ^2 = 2742.431, p<0.001) confirms that the correlation matrix is suitable for factor analysis (Bartlett, 1950) [8] (See Table 5).

Table 5: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.807
Bartlett's Test of Sphericity	Approx. Chi-Square	2742.431
	Df	10
	Sig.	0.000

Using PCA, five factors with eigenvalues greater than 1 were extracted, comprising 20 items and explaining 69.42% of the total variance (Table 6). All items recorded communalities above 0.50, indicating strong representation by the extracted components and confirming the internal consistency and validity of the construct.

Table 6: Summary of Results from Scale Purification: Communalities, Eigen Value and Explained Variance.

Factors	Item No	Elements	Communalities	Eigen Value	Explained Variance
Price	PC1	Our cost structure allows us to offer competitive prices.	0.768	2.653	55.783
	PC2	We achieve cost advantages that allow us to compete on price.	0.631		
	PC3	Our pricing strategies are supported by supply chain efficiencies.	0.512		
	PC4	We are perceived as a price leader in our industry.	0.742		
Quality	QL1	Our products consistently meet or exceed quality expectations.	0.711	2.63	65.734
	QL2	Quality is integrated across all stages of our supply chain.	0.762		
	QL3	We use quality as a source of competitive differentiation.	0.769		
	QL4	Customer feedback indicates high satisfaction with our product quality.	0.688		
Delivery Dependability	DD1	We consistently deliver products on time as promised.	0.686	2.819	76.146
	DD2	Our supply chain is reliable in meeting delivery schedules.	0.694		
	DD3	Customers trust our delivery commitments.	0.698		
	DD4	We have systems in place to avoid delivery delays.	0.741		
Product Innovation	PI1	Our company frequently introduces innovative products.	0.670	2.808	66.122
	PI2	Supply chain partners contribute to our innovation process.	0.750		
	PI3	Innovation in product design is a key differentiator for us.	0.643		
	PI4	We respond quickly to market demands with new offerings.	0.745		
Time to Market	TM1	Our supply chain supports rapid product development cycles.	0.772	2.973	56.482
	TM2	We are quicker to market compared to competitors.	0.737		
	TM3	Time-to-market is a core focus in our supply chain strategy.	0.700		
	TM4	Reduced lead times have helped us gain market advantages.	0.764		

Rotated Component Matrix of Competitive Advantage

The rotated component matrix revealed a well-defined five-factor structure representing key dimensions of competitive advantage: Price, Quality, Delivery Dependability, Product Innovation, and Time to Market. Each item demonstrated strong loadings above the acceptable threshold of 0.50 on its respective factor, indicating a high degree of consistency between the items and their underlying constructs (see Table 7).

Table 7: Rotated Component Matrix of Competitive Advantage

Item Code	Price (F1)	Quality (F2)	Delivery Dependability (F3)	Product Innovation (F4)	Time to Market (F5)
PC1	0.768				
PC2	0.631				
PC3	0.512				
PC4	0.742				
QL1		0.711			
QL2		0.762			
QL3		0.769			
QL4		0.688			
DD1			0.686		
DD2			0.694		
DD3			0.698		
DD4			0.741		
PI1				0.670	
PI2				0.750	
PI3				0.643	
PI4				0.745	
TM1					0.772
TM2					0.737
TM3					0.700
TM4					0.764

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization

Confirmatory Factor Analysis: Measurement Model Assessment

The measurement model assessment, a critical phase of Structural Equation Modelling (SEM), evaluates how well observed indicators represent their underlying latent constructs (Hair *et al*., 2019) [38]. This step ensures the validity and reliability of the constructs before proceeding to the structural model.

Factor loadings were first examined to confirm indicator relevance, with values above 0.60 deemed acceptable (Byrne, 2016) [14]. Reliability was then assessed through Cronbach's Alpha and Composite Reliability, indicating internal consistency among items. Convergent and discriminant validity were tested using Average Variance Extracted (AVE) and the Fornell-Larcker criterion, respectively, to confirm that constructs measure distinct concepts (Fornell & Larcker, 1981) [34].

This study adopted a two-stage disjoint approach, where latent variable scores from lower-order constructs were used as indicators for higher-order constructs.

Stage One: Evaluation of Lower-Order Constructs

In the first stage, the measurement quality of lower-order constructs was assessed by examining indicator loadings, Cronbach's alpha, VIF values, and Composite Reliability. Convergent validity was confirmed through AVE, while discriminant validity ensured the constructs were conceptually distinct (Hair *et al*., 2019) [38].

Factor Loadings

Factor loadings indicate the extent to which each item represents its corresponding construct, with values above 0.60 typically reflecting a strong relationship. In this study, all items exceeded this threshold, confirming their appropriateness and contributing to the model's overall reliability (Table 8).

Table 8: Factor Loadings

Item	TC	ABC	KC	OBA	PC	QL	DD	PI	TM
TC1	0.842								
TC2	0.874								
TC3	0.86								
TC4	0.889								
TC5	0.838								
ABC1		0.862							
ABC 2		0.855							
ABC 3		0.844							
ABC 4		0.83							
ABC 5		0.822							
KC1			0.87						
KC2			0.885						
KC3			0.892						
KC4			0.849						
KC5			0.764						
OBA1				0.858					
OBA2				0.877					
OBA3				0.862					
OBA4				0.834					
OBA5				0.842					
PC1					0.874				
PC2					0.863				
PC3					0.878				
PC4					0.89				
QL1						0.859			
QL2						0.868			
QL3						0.843			
QL4						0.875			
DD1							0.868		
DD2							0.887		
DD3							0.859		
DD4							0.875		
PI1								0.853	
PI2								0.871	
PI3								0.878	
PI4								0.855	
TM1									0.873
TM2									0.885
TM3									0.894
TM4									0.861

The factor loadings presented in Table 4.19 are organized into two key sections: items TC1 to OBA5 correspond to Supply Chain Cost Management Practices, while items PC1 to TM4 pertain to Competitive Advantage. Factor loadings represent the strength of association between observed items and their latent constructs, with values above 0.70 indicating strong reliability (Hair *et al*., 2011). As observed, all items meet or surpass this benchmark, confirming robust indicator reliability and a valid representation of each construct.

Indicator Multicollinearity

Multicollinearity refers to high intercorrelations among indicators, which can compromise the precision of regression estimates (Daoud, 2017). To assess this, the Variance Inflation Factor (VIF) is employed, where values below 3 are generally considered acceptable (Fornell & Bookstein, 1982; Hair *et al*., 2016). In this study, all VIF values were within the recommended threshold, indicating that multicollinearity is not a concern and that each indicator contributes uniquely to its construct (See Table 9).

Table 9: Variance Inflation Factor (VIF) Values for All Measurement Items

Item	VIF	Item	VIF	Item	VIF
TC1	2.965	KC5	2.934	DD1	2.754
TC2	3.102	OBA1	2.729	DD2	2.667
TC3	3.044	OBA 2	2.546	DD3	2.811
TC4	3.011	OBA 3	2.489	DD4	2.709
TC5	2.847	OBA 4	2.337	PI1	2.716
ABC1	2.765	OBA 5	2.529	PI2	2.684
ABC 2	2.934	PC1	2.571	PI3	2.803
ABC 3	3.011	PC2	2.481	PI4	2.745
ABC 4	2.872	PC3	2.375	TM1	2.637
ABC5	2.114	PC4	2.642	TM2	2.721
KC1	2.889	QL1	2.833	TM3	2.859
KC2	2.961	QL2	2.576	TM4	2.698
KC3	2.961	QL3	2.847		
KC4	3.076	QL4	2.642		

Reliability Analysis

Reliability refers to the extent to which a measurement tool consistently produces stable and dependable results over time. In this study, reliability was evaluated using both Cronbach's Alpha and Composite Reliability (CR). While Cronbach's Alpha assumes equal weighting of all items, CR is generally preferred as it accounts for the actual factor loadings of individual items, providing a more accurate assessment of internal consistency (Hair *et al*., 2019) [38]. For both metrics, values above 0.70 are considered acceptable, indicating that the items reliably measure their respective constructs.

Table 10: Cronbach's Alpha & Composite Reliability

S. No.	Construct			Cronbach's Alpha (>0.6 or 0.7)	Composite Reliability (>0.6 or 0.7)
2	Supply Chain Cost Management Practices (SCCMP)	Dimensions	Target Costing (TC)	0.878	0.893
			Activity Based Costing (ABC)	0.867	0.869
			Kaizen Costing (KC)	0.839	0.853
			Open Book Accounting (OBA)	0.864	0.892
3	Competitive Advantage (CA)	Dimensions	Price (PC)	0.824	0.733
			Quality (QL)	0.857	0.841
			Delivery Dependability (DD)	0.832	0.807
			Product Innovation (PI)	0.878	0.860
			Time to Market (TM)	0.846	0.800

As shown in Table 10, all lower-order constructs including the dimensions of Supply Chain Cost Management Practices and Competitive Advantage demonstrate composite reliability values above the accepted threshold, confirming the internal consistency and reliability of the measurement scales.

Construct Validity

Construct validity refers to the extent to which observed indicators truly capture the theoretical constructs they are intended to measure (Cronbach & Meehl, 1955) [24]. Within the PLS-SEM framework, construct validity is typically assessed through two key components: convergent and discriminant validity.

Convergent Validity

Convergent validity ensures that items designed to measure the same construct are strongly correlated. It is assessed using the Average Variance Extracted (AVE), where values of 0.50 or higher suggest sufficient shared variance among the indicators (Fornell & Larcker, 1981) [34], thereby confirming the adequacy of the measurement model.

Table 11: Convergent Validity of Supply chain management practices, Supply chain cost management practices and Competitive advantage

Constructs	Dimensions	Average variance Extracted (>0.5)
Supply Chain Cost Management Practices	TC	0.755
	ABC	0.708
	KC	0.691
	OBA	0.748
Competitive Advantage	PC	0.788
	QL	0.759
	DD	0.721
	PI	0.78
	TM	0.704

Average Variance Extracted (AVE)

AVE assesses the extent to which a construct explains the variance in its indicators. A value above 0.50 indicates satisfactory convergent validity (Hair *et al*., 2022). It is computed as the average of the squared factor loadings. As shown in Table 11, all constructs in this study meet this threshold, confirming adequate convergent validity.

Discriminant Validity

Discriminant validity ensures that conceptually distinct constructs do not overlap empirically. Using the Fornell and Larcker Criterion, it is confirmed when a construct's AVE exceeds the squared correlations it shares with other constructs (Fornell & Larcker, 1981) [34]. Results from the study meet this criterion, affirming the distinctiveness of each construct.

Table 12: Fornell and Larcker Criterion of Supply chain management Practices, Supply chain Cost management Practices, and Competitive Advantage

Factors	TC	ABC	KC	OBA	PC	QL	DD	PI	TM
TC	0.84								
ABC	0.67	0.83							
KC	0.66	0.65	0.82						
OBA	0.62	0.61	0.60	0.83					
PC	0.52	0.51	0.50	0.48	0.78				
QL	0.51	0.50	0.49	0.47	0.60	0.80			
DD	0.53	0.52	0.51	0.49	0.61	0.62	0.81		
PI	0.50	0.49	0.48	0.46	0.59	0.60	0.61	0.79	
TM	0.49	0.48	0.47	0.45	0.58	0.59	0.60	0.63	0.78

Fornell and Larcker Criterion

This criterion ensures that each construct is empirically unique. In this study, as indicated in Table 12, the Fornell and Larcker criterion was met, as the square roots of AVE (shown diagonally in the matrix) were higher than the inter-construct correlations, confirming that each construct shares more variance with its indicators than with others (Fornell & Larcker, 1981) [34].

Table 13: Heterotrait-Monotrait Ratio (HTMT) of Lower Order Constructs

	TC	ABC	KC	OBA	PC	QL	DD	PI	TM
TC									
ABC	0.333								
KC	0.766	0.547							
OBA	0.392	0.729	0.658						
PC	0.653	0.26	0.696	0.716					
QL	0.323	0.327	0.115	0.622	0.309				
DD	0.646	0.275	0.141	0.741	0.294	0.149			
PI	0.538	0.465	0.708	0.612	0.561	0.228	0.538		
TM	0.281	0.389	0.611	0.354	0.273	0.271	0.226	0.505	

HTMT Ratio

To strengthen this assessment, the Heterotrait-Monotrait (HTMT) ratio was also examined. All HTMT values fell below the conservative threshold of 0.85 (Henseler *et al.*, 2015) [42], reinforcing the conclusion that the constructs are clearly distinct from one another (See Table 13).

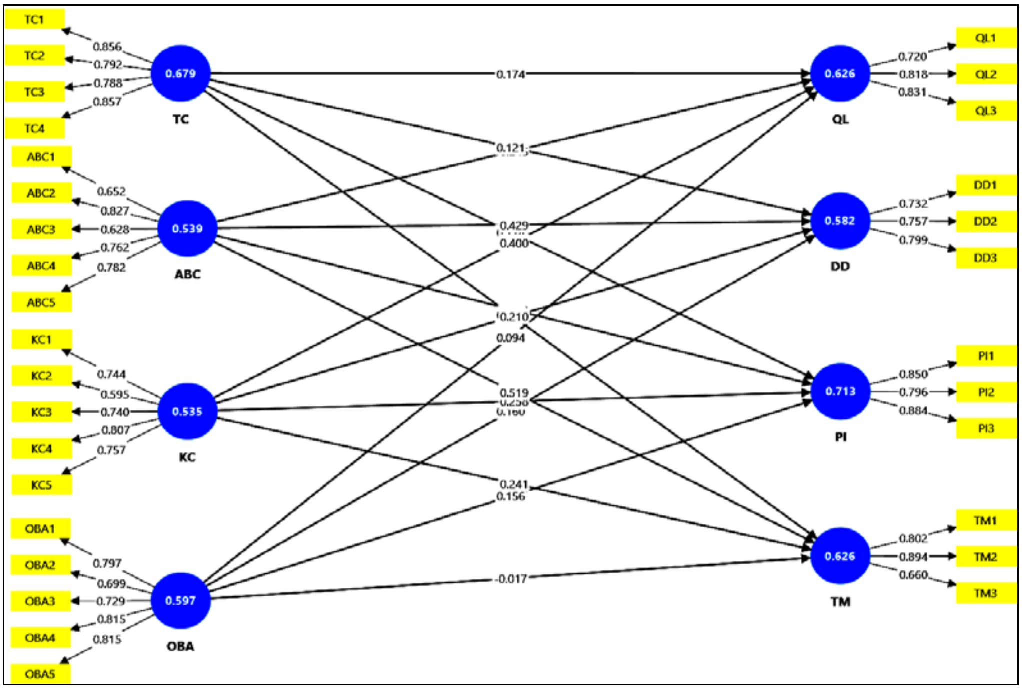

Fig 1: Measurement Model of Lower Order construct

Reflective Measurement Model and Higher-Order Construct Validation

Figure 1 illustrates the reflective measurement model, where ellipses represent latent constructs and rectangles denote observed indicators. Arrows indicate factor loadings and structural paths, while the R^2 value inside the Competitive Advantage construct reflects explained variance. All factor loadings exceed the recommended threshold, supporting the model's suitability for PLS-SEM analysis.

Validation of Higher-Order Constructs

The study models Supply Chain Management Practices and Competitive Advantage with five dimensions each, and Supply Chain Cost Management Practices with four. Reliability and validity were ensured through Cronbach's Alpha and Composite Reliability (both > 0.70), Average Variance Extracted (AVE > 0.50), and discriminant validity using Fornell-Larcker, HTMT, and cross-loadings (Hair *et al*., 2019) [38]. These results confirm the robustness and conceptual clarity of the higher-order constructs.

Table 14: Higher Order Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha ≥ 0.70	Composite Reliability ≥ .0.70	AVE ≥ 0.50
Supply chain Cost management practices (SCCMP)	0.913	0.921	0.746
Competitive Advantage (CA)	0.937	0.938	0.799

Reliability and Convergent Validity of Higher-Order Constructs

As shown in Table 14, all higher-order constructs—Supply Chain Management Practices (SCMP), Supply Chain Cost Management Practices (SCCMP), and Competitive Advantage (CA) demonstrated strong internal consistency, with Cronbach's Alpha and Composite Reliability exceeding 0.70 and AVE values above 0.50. These results confirm the reliability and convergent validity of the constructs, ensuring they effectively represent their underlying concepts.

Discriminant Validity of Higher-Order Constructs

Discriminant validity was assessed using the Fornell-Larcker criterion, HTMT ratio, and cross-loadings. All three methods confirmed that each higher-order construct is both conceptually and statistically distinct from the others.

Fornell-Larcker Criterion: This method validated discriminant validity by showing that the square root of each construct's AVE was greater than its correlations with other constructs indicating stronger relationships with their own indicators than with external constructs.

Table 15: Fornell and Larcker (1981) Criterion-Higher Order Discriminant Validity

	CA	SCCMP
CA	0.794	
SCCMP	0.624	0.764

As presented in Table 15, the square roots of AVE for the higher-order constructs Competitive Advantage (CA) and Supply Chain Cost Management Practices (SCCMP) exceed their inter-construct correlations. This satisfies criterion, confirming that each construct shares greater variance with its own indicators than with other constructs.

Heterotrait-Monotrait Ratio (HTMT)

Further confirmation of discriminant validity comes from the HTMT analysis. All HTMT values should fall below the recommended threshold of 0.90 (Henseler *et al*., 2015) [42], demonstrating that the higher-order constructs are conceptually and statistically distinct.

Table 16: HTMT-Higher Order Discriminant Validity

	CA	SCCMP
CA		
SCCMP	**0.654**	

As depicted in Table 16, the Heterotrait-Monotrait (HTMT) values for the higher-order constructs Competitive Advantage (CA), and Supply Chain Cost Management Practices (SCCMP) 0.654. Since values are comfortably below the 0.90 benchmark, thereby confirming strong discriminant validity in line with the HTMT criterion (Henseler *et al*., 2015) [42].

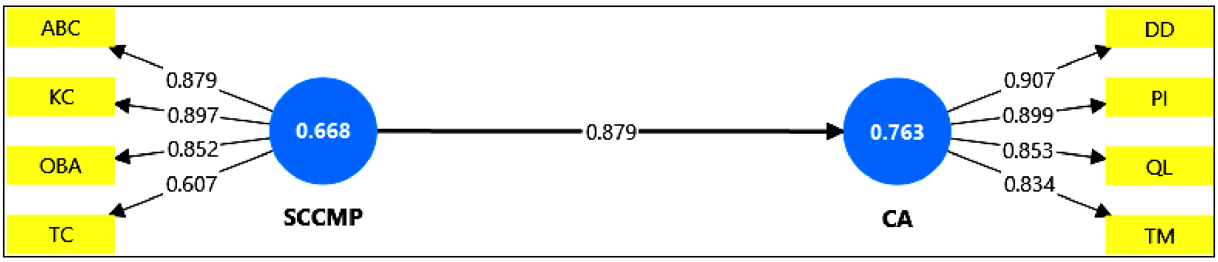

Fig 2: Measurement Model for Higher Order Constructs

Figure 2 presents the two main higher-order constructs Supply Chain Cost Management Practices (SCCMP) and Competitive Advantage (CA) represented as blue circles and measured through their respective reflective indicators shown in yellow rectangles. SCCMP includes dimensions such as Target Costing, Activity-Based Costing, Kaizen Costing, and Open Book Accounting.

In reflective models, indicators reflect the construct, with influence flowing from the latent variable to its observed measures (Garson, 2012) [35]. Outer loadings, most above 0.70, confirm strong indicator reliability. The R^2 value within the CA construct reflects the proportion of variance explained, indicating the model's predictive strength (Shmueli & Koppius, 2011; Rigdon, 2012) [68, 61].

Structural Model Assessment and Predictive Evaluation

The structural model was assessed using standard PLS-SEM criteria, including the coefficient of determination (R^2) to evaluate the model's explanatory power, the effect size (f^2) to assess the relative impact of each predictor, and the predictive relevance (Q^2) to test the model's ability to predict endogenous constructs. Bootstrapping was applied to determine the statistical significance of the hypothesized relationships.

To further enhance analytical robustness, the study also employed the PLS-Predict technique to assess out-of-sample predictive power. This method offers a practical evaluation of the model's performance on unseen data, reinforcing the reliability and applicability of the findings.

Structural Model Framework: Supply Chain Cost Management Practices and Competitive Advantage

Since objective of this study is to examine the impact of Supply Chain Cost Management Practices (SCCMP) on the Competitive Advantage (CA) of Indian automobile companies, relationship is grounded in strategic cost theory and supported by prior research that emphasizes the role of cost management techniques in driving competitive performance (Cooper & Slagmulder, 2004; Shank & Govindarajan, 1993) [21, 67].

Strategic cost tools such as Target Costing, Activity-Based Costing, Kaizen Costing, and Open Book Accounting enable firms to optimize costs across the supply chain, improve value creation, and enhance responsiveness to market changes. These practices allow firms to manage cost structures proactively, align operational decisions with strategic goals, and strengthen their positioning on dimensions such as price, quality, delivery dependability, product innovation, and time to mark*et al*l key elements of competitive advantage (Seuring, 2002; Kajüter, 2002) [65, 47].

Building on this conceptual foundation, the study investigates how effectively embedded SCCMP influences CA and proposes the following hypothesis to validate this relationship within the Indian automobile context.

Hypothesis: Supply Chain Cost Management Practices have a significant positive Impact on the Competitive Advantage of Indian automobile companies.

Structural Model Assessment

In PLS-SEM, the structural model outlines the theoretical relationships between latent constructs based on prior empirical and conceptual foundations. Unlike the measurement model, which validates the connection between observed indicators and their latent constructs, the structural model evaluates the causal pathways among the constructs themselves.

Key metrics used for assessment include:

- **R^2 (coefficient of determination)** to explain variance in endogenous constructs,
- **f^2 (effect size)** to assess the strength of each predictor's influence, and
- **Q^2 (predictive relevance)** to examine the model's capability to predict observed data (Hair *et al.*, 2019) [38].

In this study, the structural model was applied to test the hypothesized direct effects of Supply Chain Cost Management Practices (SCCMP) on Competitive Advantage (CA). Analysis was performed using SMART PLS version 4, a tool appropriate for modeling complex interrelationships in management research.

Step 1: Evaluation of Collinearity among Predictor Constructs

Before interpreting structural paths, it is important to verify that predictor constructs are not highly correlated. Collinearity can distort path coefficients and affect result reliability (Sarstedt & Mooi, 2019) [62]. This was checked using Variance Inflation Factor (VIF) values.

As per Becker *et al.* (2017) [10], VIF values below 3 indicate no collinearity concerns. In this study, all inner and outer VIF values were well below the threshold (see Table 17), confirming the model's suitability for structural analysis and the reliability of path estimates.

Table 17: Variance Inflation Factor (VIF) Values of Constructs

	CA	SCCMP
CA		
SCCMP	2.151	

Step 2: Significance and Relevance of Path Coefficients

This step assesses the strength and significance of the relationship between Supply Chain Cost Management Practices (SCCMP) and Competitive Advantage (CA) in the Indian automobile industry. Using PLS-SEM with 5,000 bootstrap samples, the path coefficient was evaluated for statistical significance and practical relevance (Hair *et al.*, 2019; Streukens & Leroi-Werelds, 2016) [38, 71]. Coefficients closer to +1 reflect stronger positive effects. The results validate the hypothesized link and reveal the influence of SCCMP on enhancing competitiveness.

Structural Model: Direct Effect of SCCMP on CA

Research Model 1 (Figure 3) illustrates the direct relationship between Supply Chain Cost Management Practices (SCCMP) and Competitive Advantage (CA), reflecting the study's aim to explore how cost management strategies enhance competitiveness in Indian automobile firms, particularly those under SIAM. To test this linkage, bootstrapping with 5,000 resamples was applied using SmartPLS v4 at a 5% significance level. The resulting estimates standard errors, t-values, and p-values are reported in Table 16 and confirm the statistical validity of the model.

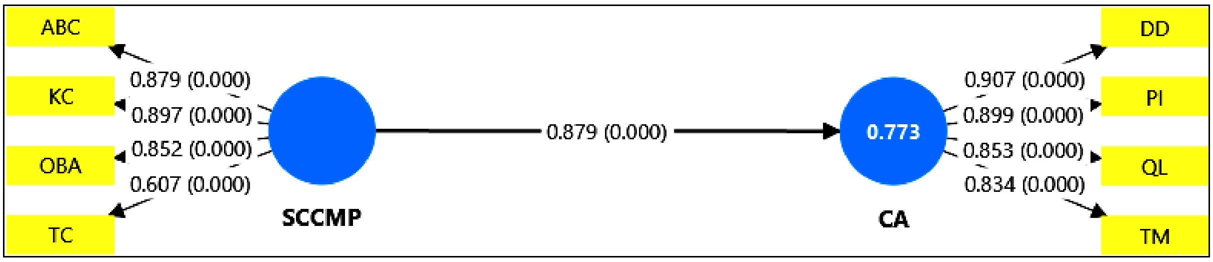

Fig 3: Structural model of SCCMP and CA

Table 18: Path coefficient and Hypothesis Testing Results

	Original sample (β)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SCCMP -> CA	0.773	0.055	9.121	0.000

The results presented in Table 18 confirm a strong and statistically significant positive relationship between Supply Chain Cost Management Practices (SCCMP) and Competitive Advantage (CA). The path coefficient (β = 0.773), along with a high t-value (9.121) and a p-value of 0.000, indicates that firms implementing effective cost management techniques such as Target Costing, Activity-Based Costing, Kaizen Costing, and Open Book Accounting are more likely to enhance their competitive positioning in the market.

This finding highlights the strategic importance of cost management in driving competitiveness. By streamlining cost structures and eliminating inefficiencies across the supply chain, organizations can achieve cost leadership, invest in innovation, and deliver greater value to customers key elements of sustained competitive advantage.

These results align with earlier empirical evidence (Mahmoud Ismail & Reddy, 2018; Devie & Kwistianus, 2023; Mahmood & Sabir, 2023; Musa & Ibrahim, 2023; Kannaiah, 2015; Idowu, 2014; Ghafeer & Mazahrih, 2014; Al-awawdeh & Al-Sharairi, 2012; Alkababji, 2023; Ali & Obaid, 2021; Khan; Al Sha'ar; Fehr & Rocha, 2018) [54, 30, 53, 57, 48, 36, 3, 5, 4, 33], reinforcing the critical role of cost-focused practices in achieving long-term strategic outcomes.

Accordingly, the hypothesis that supply chain cost management practices significantly and positively impact competitive advantage is strongly supported.

Step 3: Assessment of the Model's Explanatory Power

In PLS-SEM, evaluating a model's explanatory strength is essential to understand how well the independent variables explain variance in the dependent construct. The coefficient of determination (R^2) serves as a key metric, indicating the proportion of variance in the endogenous variable explained by its predictors (Hair *et al.*, 2022) [38]. An R^2 value closer to 1 implies a stronger model fit and better in-sample predictive power (Rigdon, 2012; Hair *et al.*, 2019) [61, 38]. According to Hair *et al.* (2019) [38], R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively.

Table 19: R square of the structural model

	R-square	R-square adjusted
CA	0.896	0.895

In this study, as revealed in Table 19, the R^2 value of 0.896 for Competitive Advantage (CA) indicates that Supply Chain Cost Management Practices (SCCMP) account for nearly 90% of the variance in CA among Indian automobile firms. This reflects a high level of explanatory power, reinforcing the model's theoretical validity and empirical strength.

Effect Size (f^2) and Predictive Relevance (Q^2) of the Structural Model

Additionally, the model's effect size (f^2) was assessed to understand the relative impact of SCCMP on CA. As per Cohen, an f^2 of 0.02 is small, 0.15 medium, and 0.35 large. This analysis helps identify how significantly SCCMP contributes to explaining competitive advantage in the sector.

Table 20: F square of the structural model

	CA	SCCMP
CA		
SCCMP	0.469	

Table 20 presents the effect size (f^2) for Supply Chain Cost Management Practices (SCCMP) in predicting Competitive Advantage (CA). Following Cohen's guidelines, the f^2 value of 0.469 represents a large effect, indicating that SCCMP plays a substantial role in enhancing competitive advantage in the Indian automobile sector. This underscores the importance of cost-focused supply chain strategies such as Target Costing, Activity-Based Costing, Kaizen Costing, and Open Book Accounting in strengthening a firm's market position.

The model's predictive relevance was further assessed using the Q^2 statistic, which evaluates the model's ability to predict outcomes for endogenous constructs. Q^2 values above zero confirm predictive accuracy (Hair *et al.*, 2022; Chin, 1998) [38, 17].

Table 21: Q-square of the structural model

Construct	Q^2 Predict
DD	0.758
PC	0.638
PI	0.750
QL	0.753
TM	0.638

As indicated in Table 21, all Q^2 values exceed the zero threshold, indicating strong predictive relevance of the model. Particularly high values for Delivery Dependability

(0.758), Product Innovation (0.750), and Quality (0.753) reflect the model's effectiveness in forecasting key dimensions of competitive advantage.

Step 4: Assessment of the Model's Predictive Power

In PLS-SEM, assessing the predictive power of a model goes beyond evaluating its explanatory strength. While the R^2 value provides insight into how well the model explains variance within the sample, it reflects only in-sample performance and not how well the model predicts new or unseen data.

To overcome this limitation, PLS-Predict, introduced by Shmueli *et al.* (2011) [68], evaluates out-of-sample predictive relevance by splitting the data into training and holdout samples. This method estimates the model on one part of the data and tests its predictive accuracy on the other mimicking real-world forecasting.

A common approach within PLS-Predict is k-fold cross-validation, typically using 10 folds (Shmueli *et al.*, 2019) [69]. In this procedure, the dataset is divided into ten equal parts, and the model is iteratively trained on nine folds while predicting the tenth. This ensures each observation is tested by a model that did not use it during estimation, offering an unbiased evaluation of predictive accuracy.

Key metrics used to assess prediction quality include:

- Root Mean Squared Error (RMSE) - preferred for general evaluation.
- Mean Absolute Error (MAE) - used when errors are skewed.

The model's predictive strength is then compared to a linear regression benchmark (LM). According to Shmueli *et al.* (2019) [68]:

- **High predictive power:** All indicators in the PLS-SEM model outperform LM.
- **Moderate:** Most indicators perform equally or better.
- **Low:** Few indicators exceed the LM benchmark.

This approach strengthens the credibility of the model by ensuring it performs reliably not only within the sample but also when applied to new data.

Table 22: PLS-Predict of the Model

Construct	PLS-SEM_RMSE	LM_RMSE	Difference (PLS - LM)
DD	0.496	0.5	-0.004
PC	0.606	0.668	-0.062
PI	0.503	0.534	-0.031
QL	0.499	0.518	-0.019
TM	0.606	0.64	-0.034

The results in Table 22 indicate that all indicators in the PLS-SEM model exhibit lower Root Mean Squared Error (RMSE) values than those in the linear regression benchmark. This consistent pattern confirms that the model possesses high predictive power, demonstrating its effectiveness in forecasting outcomes beyond the estimation sample.

Conclusion

This study provides robust empirical evidence on the critical role of Supply Chain Cost Management Practices (SCCMP) in shaping the competitive advantage of Indian automobile companies. Through a structured PLS-SEM analysis, the research validates that practices such as Target Costing, Activity-Based Costing, Kaizen Costing, and Open Book Accounting significantly enhance a firm's ability to compete on key performance dimensions including price, quality, delivery dependability, product innovation, and time to market.

The structural model demonstrated strong explanatory power, with an R^2 value of 0.896, indicating that SCCMP accounts for nearly 90% of the variance in competitive advantage. Furthermore, the effect size ($f^2 = 0.469$) confirmed a substantial impact, while the Q^2 values indicated excellent predictive relevance across all dimensions of competitive advantage.

The use of PLS-Predict added another layer of rigor by confirming the model's high out-of-sample predictive accuracy, thereby reinforcing its practical utility for real-world strategic decision-making.

Importantly, these findings bridge a crucial gap in supply chain and management accounting literature by empirically linking cost-focused supply chain strategies to firm-level competitive outcomes particularly in the under-explored context of emerging economies like India.

By emphasizing transparency, collaboration, and continuous cost improvement across the value chain, the study highlights that strategic cost management is not merely a financial control mechanism but a powerful enabler of sustained competitiveness. These insights hold significant implications for both practitioners and policymakers seeking to enhance the performance and global positioning of India's manufacturing sector.

Future research can extend this framework by incorporating additional sectors, exploring longitudinal effects, and examining digital enablers of cost management across supply networks.

References

1. Agrawal P, Mehra S. Just-in-time and total quality management: A survey of the literature. Int J Qual Reliab Manag. 1998;15(6):399-414.
2. Al Sha'ar Y. Cost accounting practices and their impact on performance: Evidence from Jordanian manufacturing firms. Int J Econ Commer Manag. 2016;4(10):23-36.
3. Al-awawdeh WM, Al-Sharairi MS. The impact of cost accounting information on managerial decision-making: A case study of manufacturing firms. Int J Bus Soc Sci. 2012;3(18):243-51.
4. Ali HY, Obaid T. Strategic cost management and firm performance: Empirical evidence from Iraqi companies. J Asian Finance Econ Bus. 2021;8(3):789-96.
5. Alkababji A. Strategic cost management practices and performance: An empirical investigation in the industrial sector. J Account Organ Change. 2023;19(1):110-25.
6. Axelsson B, Rozemeijer F, Wynstra F. Developing sourcing capabilities: Creating strategic change in purchasing and supply management. Wiley; 2002.
7. Bagchi PK, Skjoett-Larsen T. Integration of information technology and organizations in a supply chain. Int J Logist Manag. 2002;13(1):91-107.

8. Bartlett MS. Tests of significance in factor analysis. Br J Stat Psychol. 1950;3(2):77-85.
9. Baruch Y, Holtom BC. Survey response rate levels and trends in organizational research. Hum Relat. 2008;61(8):1139-60.
10. Becker JM, Ringle CM, Sarstedt M, Völckner F. How collinearity affects mixture regression results. Mark Lett. 2015;26(4):643-59.
11. Blocher EJ, Stout DE, Cokins G. Cost management: A strategic emphasis. McGraw-Hill/Irwin; 2002.
12. Bommer M, O'Neil B, Treat S. Strategic assessment of supply chain management. Bus Process Manag J. 2001;7(2):133-44.
13. Bromwich M, Bhimani A. Management accounting: Evolution not revolution. Chartered Institute of Management Accountants; 1989.
14. Byrne BM. Structural equation modeling with AMOS: Basic concepts, applications, and programming. 3rd ed. Routledge; 2016.
15. Cerny BA, Kaiser HF. A study of a measure of sampling adequacy for factor-analytic correlation matrices. Multivariate Behav Res. 1977;12(1):43-47.
16. Chandra C, Kumar S. Supply chain management in theory and practice: A passing fad or a fundamental change? Ind Manag Data Syst. 2000;100(3):100-14.
17. Chin WW. The partial least squares approach to structural equation modeling. In: Marcoulides GA, editor. Modern methods for business research. Lawrence Erlbaum Associates; 1998. p. 295-336.
18. Chivaka R. Partnering for value: Strategic cost management in supply chains. Supply Chain Manag Int J. 2015;20(2):152-69.
19. Choi TY, Hong Y. Unveiling the structure of supply networks: Case studies in Honda, Acura, and DaimlerChrysler. J Oper Manag. 2003;20(5):469-93.
20. Cooper R, Slagmulder R. Strategic cost management: Concepts, techniques, and applications. Free Press; 1998.
21. Cooper R, Slagmulder R. Interorganizational cost management and relational context. Account Organ Soc. 2004;29(1):1-26.
22. Cooper R, Yoshikawa T. Inter-organizational cost management systems: The case of the Tokyo-Yokohama-Kanagawa automobile industry. Int J Prod Econ. 1994;37(1):29-44.
23. Cooper WW, Seiford LM, Zhu J. Data envelopment analysis: History, models, and interpretations. Springer; 2015.
24. Cronbach LJ, Meehl PE. Construct validity in psychological tests. Psychol Bull. 1955;52(4):281-302.
25. Cullen J, Johnson JL, Storey J. Managing inter-firm relationships in a period of technological change. Technol Anal Strateg Manag. 1999;11(1):5-28.
26. Daoud JI. Multicollinearity and regression analysis. J Phys Conf Ser. 2017;949(1):012009.
27. Dekker HC. Value chain analysis in interfirm relationships: A field study. Manag Account Res. 2003;14(1):1-23.
28. Dekker HC. Control of inter-organizational relationships: Evidence on appropriation concerns and coordination requirements. Account Organ Soc. 2004;29(1):27-49.
29. Dekker H, Van Goor AR. Supply chain management and management accounting: A literature review and case study. Logistiek Manag. 2000;7(1):20-27.
30. Devie D, Kwistianus A. The effect of cost management practices on firm performance: Evidence from Indonesia. J Financ Rep Account. 2023;21(1):111-28.
31. Etikan I, Musa SA, Alkassim RS. Comparison of convenience sampling and purposive sampling. Am J Theor Appl Stat. 2016;5(1):1-4.
32. Ezzamel M, Lilley S, Willmott H. The character and role of strategy in management control. Account Organ Soc. 1990;15(1-2):105-28.
33. Fehr E, Rocha F. Behavioural foundations of cost management practices. Manag Account Res. 2018;39:33-47.
34. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39-50.
35. Garson D. Testing statistical assumptions. Statistical Associates Publishing; 2012.
36. Ghafeer N, Mazahrih T. The effect of using target costing in Jordanian manufacturing companies. Eur J Bus Manag. 2014;6(12):64-71.
37. Goldbach M. Target costing and ABC—A case from German automotive industry. Cost Manag. 2002;16(2):34-42.
38. Hair JF, Hult GTM, Ringle CM, Sarstedt M. A primer on partial least squares structural equation modeling (PLS-SEM). 2nd ed. SAGE Publications; 2017.
39. Hair JF, Sarstedt M, Ringle CM, Gudergan SP. Advanced issues in partial least squares structural equation modeling. 2nd ed. SAGE Publications; 2021.
40. Hakansson H, Lind J. Accounting and network coordination. Account Organ Soc. 2004;29(1):51-72.
41. Harland CM. Supply chain management: Relationships, chains and networks. Br J Manag. 1996;7(S1):S63-80.
42. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci. 2015;43:115-35.
43. Hopwood AG. Looking across rather than up and down: On the need to explore the lateral processing of information. Account Organ Soc. 1996;21(6):589-90.
44. Idowu A. Strategic cost management practices and performance: A study of manufacturing firms in Nigeria. Int J Account Res. 2014;2(2):24-35.
45. Johnson HT, Kaplan RS. Relevance lost: The rise and fall of management accounting. Harvard Business School Press; 1987.
46. Johnson ME, Lawrence PR. Planning for manufacturing flexibility: Why it's needed and how to get it. Harv Bus Rev. 1988;66(4):94-103.
47. Kajüter P. Management control in supply chains and inter-firm networks. In: Seuring M, *et al.*, editors. Cost management in supply chains. Physica-Verlag HD; 2002. p. 15-42.
48. Kannaiah D. Strategic cost management techniques in Indian manufacturing firms. Asian J Manag Res. 2015;6(1):51-59.
49. Kaplan RS. The evolution of management accounting. Account Rev. 1984;59(3):390-418.
50. Kaplan RS. One cost system isn't enough. Harv Bus

Rev. 1988;66(1):61-66.
51. Kothari CR. Research methodology: Methods and techniques. 2nd ed. New Age International; 2004.
52. Lockamy A, Smith W. Target costing for supply chain management: Criteria and selection. Ind Manag Data Syst. 2000;100(5):210-18.
53. Mahmood R, Sabir HM. Cost management strategies and competitive advantage. Int J Manag Stud. 2023;10(2):101-17.
54. Mahmoud Ismail S, Reddy K. The role of cost management in competitive advantage. Int J Econ Financ Issues. 2018;8(5):45-52.
55. Malhotra NK, Dash S. Marketing research: An applied orientation. 7th ed. Pearson Education India; 2016.
56. Margretta J. The power of virtual integration: An interview with Dell Computer’s Michael Dell. Harv Bus Rev. 1998;76(2):73-84.
57. Musa A, Ibrahim M. Cost practices and performance: An empirical study. Int J Bus Econ Sci. 2023;14(1):63-74.
58. Patton MQ. Qualitative research and evaluation methods. 4th ed. SAGE Publications; 2014.
59. Poirier CC. Advanced supply chain management: How to build a sustained competitive advantage. Berrett-Koehler Publishers; 1998.
60. Rebitzer JB. Life-cycle costing: A review. Cost Manag. 2002;16(4):45-53.
61. Rigdon EE. Rethinking partial least squares path modeling: In praise of simple methods. Long Range Plann. 2012;45(5-6):341-58.
62. Sarstedt M, Mooi E. A concise guide to market research. 3rd ed. Springer; 2019.
63. Scapens RW. Broadening the scope of management accounting: From a microeconomic to a broader business perspective. Br Account Rev. 1999;31(3):205-25.
64. Seal W, Cullen J, Dunlop A, Berry T, Ahmed M. Enacting a European supply chain: A case study on the role of management accounting. Manag Account Res. 1999;10(3):303-22.
65. Seuring S. The product- and process-oriented approach to supply chain cost management. J Bus Logist. 2002;23(2):81-104.
66. Shank JK. Strategic cost management: New wine, or just new bottles? J Manag Account Res. 1989;1(1):47-65.
67. Shank JK, Govindarajan V. Strategic cost management: The new tool for competitive advantage. Free Press; 1993.
68. Shmueli G, Koppius OR. Predictive analytics in information systems research. MIS Q. 2011;35(3):553-72.
69. Shmueli G, Ray S, Velasquez Estrada JM, Chatla SB. The elephant in the room: Predictive performance of PLS models. J Bus Res. 2019;104:450-60.
70. Slagmulder R. Managing cost in the supply chain: Target costing in practice. Cost Manag. 2002;16(3):36-47.
71. Streukens S, Leroi-Werelds S. Bootstrapping and PLS-SEM: A step-by-step guide. Eur Manag J. 2016;34(6):618-32.
72. Suhong Li, Ragu-Nathan B, Ragu-Nathan TS, Rao SS. The impact of supply chain management practices on competitive advantage and organizational performance. Omega. 2006;34(2):107-24.
73. Thatte AA, Mukherjee A, Monplaisir L. Influence of SCM practices on SCM capabilities and performance. Oper Supply Chain Manag Int J. 2013;6(2):54-63.