Gearing Up for the Digital Age: Leveraging Transformational Capabilities and Ambidexterity for Innovation in Automotive Parts

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Abstract

This study examines how automotive parts manufacturers can leverage transformational leadership and organizational ambidexterity to drive digital innovation in the rapidly evolving Indonesian automotive industry landscape. Drawing on upper echelon and resource-based theories, the research surveyed top management from 100 Indonesian automotive component firms using a structured questionnaire. Data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The study found that while organizational ambidexterity significantly impacts digital innovation performance, transformational leadership indirectly influences it through ambidexterity. Specifically, transformational leadership had a strong positive effect on organizational ambidexterity (path coefficient = 0.678), which in turn significantly influenced innovation performance (path coefficient = 0.803). These findings highlight the crucial role of fostering organizational ambidexterity in balancing exploration of new digital technologies with exploitation of existing capabilities. The results offer evidence-based strategies for enhancing digital innovation in the automotive parts sector, emphasizing the importance of leadership in cultivating an adaptable organizational culture. This research contributes to understanding leadership dynamics and digital transformation in emerging markets' automotive supply chains, with implications for similar industries navigating technological disruption. The study's findings can guide automotive component manufacturers in developing leadership and organizational strategies to improve their innovation performance and competitiveness in the digital age.

Keywords

Organizational Ambidexterity, Digital Transformational Capability, Innovation Performance, Competitive Advantage

1. Introduction

The automotive industry is undergoing a profound digital transformation, driven by disruptive technologies and changing consumer preferences. Connected, autonomous, shared, and electric (CASE) vehicles are reshaping the automotive landscape, compelling manufacturers and suppliers to rapidly innovate [1],[2]. In this dynamic environment, automotive component manufacturers face mounting pressure to leverage digital capabilities for innovation across various business dimensions to remain competitive [3],[4]. This study examines the influence of digital transformational capability on innovation performance in the automotive components industry, with a specific focus on the mediating role of organizational ambidexterity. The automotive components sector faces particular challenges in digital transformation, including the need to integrate digital technologies into physical products and adapt to changing supply chain dynamics [5] . Firms must balance the exploration of new digital technologies with the exploitation of existing capabilities, aligning with the core concept of organizational ambidexterity [6] .

Transformational leaders play a key role in fostering a culture of digital innovation and guiding organizations through digital transformation [7],[8]. Digital transformational capability, encompassing a firm's ability to leverage digital technologies for business model innovation, has emerged as a critical factor in driving competitive advantage [9],[10]. Organizational ambidexterity has been found to be crucial for firms undergoing digital transformation, allowing them to simultaneously explore new digital innovations while exploiting existing competencies. Drawing upon Dynamic Capability theory and the Resource-Based View , this research investigates how automotive component manufacturers can effectively develop and deploy digital capabilities to enhance innovation outcomes. The resource-based view posits that firms can achieve sustainable competitive advantage by possessing and effectively utilizing valuable, rare, and inimitable resources, such as organizational ambidexterity, which enables firms to simultaneously pursue exploratory and exploitative activities and enhances innovation performance. Crucially, this study explores the mediating role of organizational ambidexterity - the ability to simultaneously pursue exploratory and exploitative activities , - in the relationship between digital transformational capability and innovation performance. While previous research has highlighted the importance of digital capabilities in enhancing innovation outcomes across industries ,, the specific dynamics within the automotive components sector warrant further investigation.

This research provides insights into how firms in emerging markets like Indonesia navigate digital transformation, addressing a gap in the literature which has primarily focused on developed economies . The integration of Upper Echelon, Dynamic Capability, and Resource-Based View theories provides a robust framework for understanding how leadership and organizational capabilities drive digital innovation in rapidly evolving markets. By examining these relationships, this research aims to provide valuable insights for practitioners and policymakers in the automotive components industry, offering guidance on how to effectively leverage digital transformational capabilities and organizational ambidexterity to drive innovation performance and sustain competitive advantage amidst technological disruptions and environmental dynamism.**2.**

2. Hypothesis Development

2.1 Digital transformational capability effect on organizational ambidexterity

The resource-based view and dynamic capabilities perspectives suggest that digital transformational capability and organizational ambidexterity are strategic resources enabling competitive advantage [8], [7]. In the automotive components industry, digital transformational capability enables firms to sense and seize digital opportunities, while organizational ambidexterity allows balancing exploration and exploitation activities [1], [2]. Empirical evidence supports a positive relationship between digital transformational capability and organizational ambidexterity [15], [17], indicating these capabilities are intertwined and mutually reinforcing. Thus, it can be hypothesized that digital transformational capability positively affects organizational ambidexterity in the automotive components industry.

(H1) : Transformational leadership is positively related to organizational ambidexterity in the automotive components industry.

2.2 Digital transformational capability effect on innovation performance.

The strategic management literature recognizes digital transformational capability as a crucial driver of firm performance and innovation [5], [6]. Through the resource-based view, this capability is considered a valuable and rare resource [8], [16], while the dynamic capabilities perspective emphasizes its role in adapting to rapidly changing environments [7]. In the automotive components industry, digital transformational capability enables firms to sense and seize digital opportunities, transforming business models and processes [15], 17]. Empirical evidence supports a positive relationship between digital transformational capability and innovation performance [6], [17], suggesting a positive effect in the automotive components context.

(H2) : Digital transformational capability is positively associated with innovation performance in the automotive components industry.

2.3 Organizational ambidexterity effect on innovation performance

Organizational ambidexterity, the ability to simultaneously pursue exploratory and exploitative activities, is positively related to innovation performance in the automotive components industry [12], [13], [12], [7], [18], [19], [20]. As a valuable, rare, and imperfectly imitable resource, organizational ambidexterity contributes to competitive advantage by balancing the exploitation of existing competencies and the exploration of new opportunities, enhancing innovation performance [8], [16], [19]. Viewed as a dynamic capability, it enables firms to sense and seize opportunities for incremental and radical innovation, adapting to dynamic market conditions [7], [18]. Empirical evidence supports the positive relationship between organizational ambidexterity and innovation performance across industries, including the automotive components industry undergoing digital transformation [19], [20], [1], [2].

(H3): Organizational ambidexterity is positively related to innovation performance in the automotive components industry.

2.4 Digital transformational capability and innovation performance mediated by organizational ambidexterity

Digital transformational capability, a dynamic capability grounded in the resource-based view, positively impacts innovation performance through the mediating role of organizational ambidexterity in the automotive components industry undergoing digital transformation [8], [21], [7], [20], [18], [21], [22]. This mediating mechanism allows firms to balance exploration (digital transformation) and exploitation (leveraging existing resources) for innovation success [18], [23].

(H4) : The relationship between digital transformational capability and innovation performance is mediated by organizational ambidexterity in the automotive components industry.

3. Research methodology

3.1 The conceptual framework

The conceptual framework, illustrated in Fig. 1, investigates the relationships between digital transformational capability, organizational ambidexterity, and innovation performance, where H1 examines whether digital transformational capability contributes to organizational ambidexterity, H2 explores the effect of digital transformational capability on innovation performance, H3 assesses the impact of organizational ambidexterity on innovation performance, and H4 investigates the potential mediating role of organizational ambidexterity in the relationship between digital transformational capability and innovation performance.

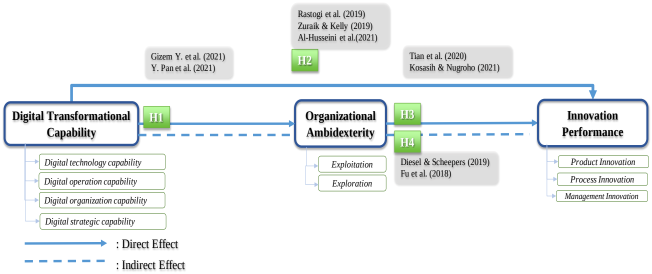

Fig. 1. The conceptual framework

3.2 Research instrument

The study will adapt validated scales to measure key variables. Digital transformational capability will be assessed using [24] scale, which captures dimensions such as digital strategy, operations, culture, and talent management. Organizational ambidexterity will be measured using scales proposed by [26], [27]. Innovation performance will be evaluated using [25] scale, which encompasses various dimensions of innovation outcomes. The research instrument will incorporate these established scales with minor adaptations for the specific context. Respondents will rate their agreement using a multi-point Likert scale. Control variables and demographic questions will account for potential confounding factors.

The questionnaire comprehensively assesses digital transformation in automotive companies through 30 questions across three key areas: (1) Digital Transformational Capability (13 questions): Evaluates digital technology, operations, organization, and strategy capabilities. (2) Organizational Ambidexterity (8 questions): Measures exploitation and exploration activities. (3) Innovation Performance (9 questions): Assesses product, process, and management innovations. This structured approach provides a holistic view of how automotive companies are adapting to and leveraging digital technologies to enhance their operations, balance existing and new capabilities, and drive innovation across multiple dimensions

3.3 Population and sample

This study targets 319 companies from the Indonesian Ministry of Industry database from Kemenperin.go.id on 2020, focusing on top management personnel. Following [28] guidelines for PLS-SEM analysis, the minimum required sample size is 40, based on ten times the largest number of structural paths pointing to a construct. To enhance precision and reliability, the sample size was increased to 100 respondents. This approach aligns with best practices in PLS-SEM research [28].

3.4 Data collection

The study targeted top management personnel from Indonesia's automotive components industry. Data collection involved surveys with questionnaires designed to capture respondents' perceptions on relevant indicators, formulated based on theoretical frameworks and expert consultations [28]. Questionnaires were distributed via email and professional networks, leveraging industry associations to enhance reach and response rates [29].

4. Result

4.1 Descriptive statistics

The study analyzed 100 valid questionnaires. Demographic data showed that 87% of respondents were male, and 73% had over 5 years of experience in automotive component companies. The respondents' positions were distributed as follows: 14% President Directors, 14% Vice President Directors, and 72% Directors. Additionally, 44% of the companies represented had between 101-500 employees.

4.2 Measurement model analysis

4.2.1 Descriptive statistics dan Convergent validity test

The measurement model analysis, crucial for evaluating construct validity and reliability, was conducted at both dimension and variable levels due to the second-order factor structure [32]. Results in Table 2 confirm the model's reliability and validity. At the dimension level, outer loadings (0.730-0.958) exceed the 0.70 threshold, indicating valid indicators [33]. Reliability is demonstrated by Cronbach's Alpha, Rho A, and Composite Reliability values above 0.70, showing acceptable internal consistency [33]. Convergent validity is established with AVE values surpassing 0.50 [33].

At the variable level, outer loadings (0.730-0.958) also exceed 0.70. Reliability measures are above 0.90, indicating excellent internal consistency. AVE values (0.593-0.652) establish convergent validity. Descriptive statistics reveal high mean values (5.177-5.450) for research variables and dimensions, suggesting well-established processes of digital transformational capability, organizational ambidexterity, and innovation performance in the sampled companies. Consistent variability across constructs is indicated by similar relative standard deviation values. These results show the measurement model's strength, laying a solid groundwork for further analysis. The high reliability and validity scores at both the dimension and variable levels confirm that the constructs are accurately measured and distinct, improving the research's overall quality and credibility.

Table 2 : Statistic descriptif and convergent validity test

Dimension	Item	Mean	Std Dev.	Outer Loading	Cronbach's Alpha	Rho A	Composite Reliability	AVE
Digital Technology Capability	3	5,223	0,417	0,934 - 0,958	0,944	0,944	0,964	0,900
Digital Operation Capability	3	5,177	0,382	0,744 - 0,919	0,776	0,805	0,870	0,693
Digital Organization Capability	4	5,230	0,421	0,795 - 0,902	0,88	0,884	0,918	0,736
Digital Strategic Capability	2	5,190	0,393	0,870 - 0,922	0,759	0,791	0,891	0,804
Exploitation	4	5,450	0,498	0,790 - 0,884	0,851	0,854	0,900	0,692
Exploration	4	5,315	0,465	0,871 - 0,922	0,913	0,913	0,939	0,793
Product Innovation	3	5,260	0,516	0,846 - 0,921	0,87	0,873	0,921	0,795
Process Innovation	3	5,293	0,511	0,810 - 0,929	0,862	0,863	0,916	0,786
Management Innovation	3	5,240	0,666	0,730 - 0,884	0,765	0,781	0,865	0,683
Variable	**Dimension**	**Mean**	**Std Dev.**	**Outer Loading**	**Cronbach's Alpha**	**Rho A**	**Composite Reliability**	**AVE**
Digital Transformational Capability	4	5,205	0,406	0,744 - 0,958	0,937	0,943	0,947	0,602
Innovation Performance	3	5,264	0,569	0,730 - 0,929	0,913	0,92	0,929	0,593
Organizational Ambidexterity	2	5,383	0,486	0,730 - 0,929	0,923	0,931	0,937	0,652

4.2.2 Discriminant validity

Based on Table 3 and Fig. 2 Both HTMT and Fornell-Larcker methods demonstrated satisfactory discriminant validity. HTMT values were below 0.90, and Fornell-Larcker criterion showed each variable's AVE root exceeded its correlations with others. This indicates the variables effectively measure distinct concepts without significant overlap, supporting the model's construct validity.

Table 3 : Discriminant validity

	Digital Transformational Capability	Innovation Performance	Organizational Ambidexterity
Digital Transformational Capability	0,776	**0,836**	**0,818**
Innovation Performance	0,773	0,770	**0,965**
Organizational Ambidexterity	0,775	0,900	0,807

Diagonal = root of AVE, value above the diagonal = HTMT and value below the diagonal = correlation

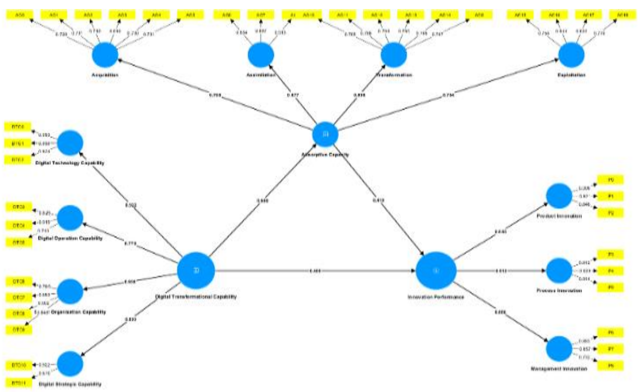

Fig. 2. PLS Model Estimation

4.3. Structural model analysis

The structural model evaluation showed that digital transformational capability significantly increases organizational ambidexterity (H1) with a path coefficient of 0.775 and a high effect size of 1.500. Digital transformational capability also has a significant direct effect on innovation performance (H2) with a path coefficient of 0.190 and a low effect size of 0.083 ($p>0.05$). Organizational ambidexterity significantly affects innovation performance (H3) with a path coefficient of 0.753 and a high effect size of 1.298. Mediation testing (H4) confirmed that organizational ambidexterity partially mediates the relationship with a high mediation effect size of 0.563 [28], [34]. The R square values indicate moderate (0.600) and high (0.825) influences for organizational ambidexterity and innovation performance, respectively, with predictive relevance [35].

Table 4 : Hypothesis Result

Hypothesis	Hypothesis Statement	Original sample (O)	T statistics (|O/STDEV|)	P-value	F Square	R Square	Q^2 Predict
H1	Digital Transformational Capability -> Organizational Ambidexterity	0,775	16,560	0,000	1,500	0,600	0,540
H2	Digital Transformational Capability -> Innovation Performance	0,190	1,980	0,048	0,083	0,825	0,496
H3	Organizational Ambidexterity -> Innovation Performance	0,753	9,111	0,000	1,298	0,825	0,496
H4	Digital Transformational Capability -> Organizational Ambidexterity -> Innovation Performance	0,583	7,909	0,000	0,563		

4.3.1. Goodness of fit model test

Table 5 : Goodness of fit model test

Goodness of Fit Index	**SRMR**	**Evaluasi CVPAT**						
		Variable	PLS-SEM vs. Indicator average (IA)			PLS-SEM vs. Linear model (LM)		
			Average loss difference	t value	p value	Average loss difference	t value	p value
0,6795	0,083	Innovation Performance	-0,043	3,258	0,003	-0,006	3,855	0
		Organizational Ambidexterity	-0,032	3,945	0,001	-0,027	4,53	0

The SEM PLS model evaluation shows a high goodness of fit index (GoF Index = 0.680), exceeding the 0.36 threshold for high GoF (Wetzels et al., 2009). The SRMR measure of 0.083 indicates an acceptable fit [37]. The PLS Predict analysis reveals that the PLS model has higher predictive power than the linear model (LM), with lower RMSE and MAE values [38]. Additionally, the CVPAT results show a negative average loss difference with $p<0.05$, confirming the model's strong predictive power compared to IA and LM benchmarks [39], [40].

5. Conclusion

Digital transformation and organizational ambidexterity are key drivers of innovation in the automotive industry. Firms must balance digital capabilities with exploration and exploitation to stay competitive. Managers should invest in technology, adaptive leadership, and workforce training. This approach aligns with dynamic capabilities and resource-based views, providing a strategic roadmap for sustained innovation and competitiveness.

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