

Customer Management and Corporate Financial Performance: The Significance of Industry 4.0 Adoption

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Abstract

A massive volume of research advance Industry 4.0 (Ind4) technologies, yet their impact on corporate financial performance (CFP) remains relatively unexplored. This study proposes a model to investigate how Ind4 Adoption level (Ind4AL) affects CFP through customer management performance (CMP). Using survey data from 91 manufacturing firms spanning 14 industries and analyzing it through bootstrap-based structural equation modeling (SEM) with 5,000 samples, we find that Ind4AL positively moderates the CMP–CFP relationship. However, the direct effects of Ind4AL on CMP and CFP are not significant. Our findings suggest that companies with higher Ind4 implementation realize stronger financial returns from effective customer management. Finally, we discuss implications for both management practice and future research directions.

Keywords

Industry 4.0 adoption, Smart factory, customer management, Financial performance, Performance measurement

1. Introduction

Advances in communication and information technologies are fundamentally changing the way businesses operate—shaping how value is created, how people work, and how they connect and communicate (Chen, 2021). These shifts are pushing companies, especially in manufacturing, into what's widely known as the next industrial revolution: Industry 4.0 (Ind4), or smart manufacturing, built around cyber-physical systems. Given its sweeping impact, it's no surprise that Ind4 has drawn increasing interest not just in business, but also across fields like engineering, science, and the social sciences (e.g., Akdil et al., 2018; Hermann et al., 2016; Moeuf et al., 2017).

A growing body of research explores how to implement Ind4 technologies effectively and examines their impact on production and operational systems. For instance, Brougham and Haar (2017) introduced a framework to assess how employees perceive the risk of job loss due to automation. Drawing from a comprehensive review of existing studies, Mayr et al. (2018) identify various linkages between lean manufacturing and Ind4 technologies, highlighting specific digital tools that can facilitate the application of eight distinct lean practices.

Büchi et al. (2020) use regression techniques to explore the relationship between Ind4 implementation and performance outcomes in smart manufacturing. Analyzing data from 231 manufacturing sites, they find that adopting Ind4 technologies has a notable positive impact on organizational performance, particularly in terms of seizing new business opportunities. Based on a systematic analysis of 186 articles, Zheng et al. (2021) investigate how various Ind4 technologies are utilized throughout manufacturing business processes. Their findings show widespread adoption of tools like IoT, big data analytics, and cloud computing—especially in production planning—while areas such as blockchain remain less examined, indicating opportunities for future research.

Subsequent work by Senna et al. (2022) examines the interrelationships among barriers to Industry 4.0 adoption in manufacturing companies using interpretive structural modelling. They find that standardization issues and the lack of off-the-shelf solutions are foundational obstacles, while organizational challenges exhibit high dependence but low driving power—contradicting earlier research. Pozzi et al. (2023) investigate eight Ind4 implementation cases within manufacturing firms, using structured interviews and site visits to uncover critical success factors. Their analysis underscores the importance of lean practices, strong leadership, cross-functional collaboration, and thorough preparation in achieving effective adoption.

Recently, Piccarozzi et al. (2024) use content analysis of sustainability reports from the 50 most innovative firms (based on Boston Consulting Group’s 2022 ranking) to explore how Ind4 enabling technologies contribute to operational sustainability. Their findings reveal that these technologies play a strategic role in advancing corporate sustainability agendas through digital innovation. More recently, Rehman et al. (2025) apply structural equation modeling (SEM) to examine how Ind4 technologies impact company operational performance, using data from 301 exporting firms. Their findings show that most Ind4 technologies, excluding machine learning, positively influence international operational competitiveness, with ambidextrous dynamic capabilities serving as a key mediator.

Although a substantial body of research exists on Ind4, much of it focuses on technological advancements—such as big data analytics, simulation, system integration, IoT, cybersecurity, cloud computing, and additive manufacturing (e.g., Mayr et al., 2018; Rossit et al., 2019; Yu et al., 2024)—or explores their implications for production and operational efficiency (e.g., Büchi et al., 2020; Piccarozzi et al., 2024; Rehman et al., 2025). Relatively few studies examine the financial implications of Ind4. Little is thus known about how varying levels of Ind4 adoption affect financial outcomes. Consequently, there appears to be a dearth of studies examining the relationships among Ind4 adoption level (Ind4AL), customer management performance (CMP), and corporate financial performance (CFP).

2. Research Hypotheses

To investigate the relationships among Ind4AL, CMP, and CFP, we propose a three-dimensional research model, as shown in Figure 1. The model is based on the premise that Ind4AL not only amplifies potential financial returns through CMP but also exerts a direct impact on both CMP and CFP. In other words, we argue that CMP has a stronger positive effect on CFP when Ind4AL is higher, and that Ind4AL directly influences both CMP and CFP.

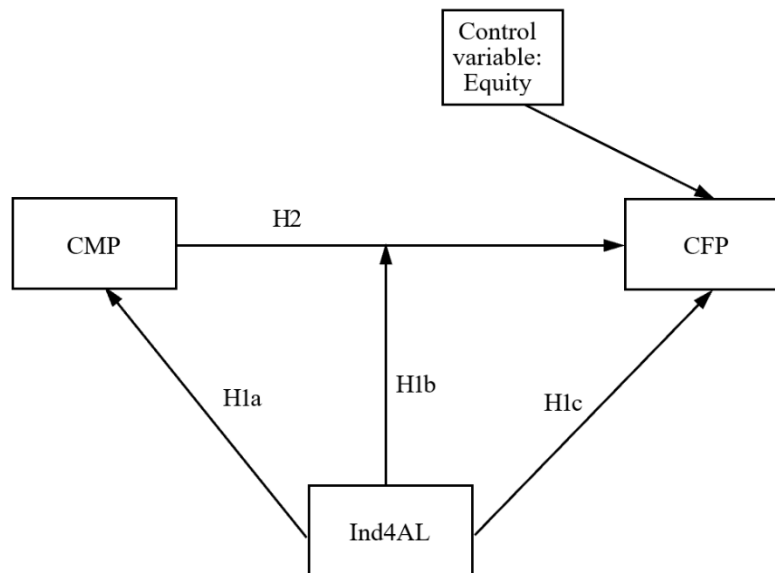


Figure 1. Hypothesized model

In Ind4 environments, manufacturing companies increasingly depend on open, interconnected systems that enable real-time communication between machines. These networks support efficient data exchange both within internal processes and across organizational boundaries in broader value chain ecosystems (Ivanov et al., 2016). Given this

high level of interconnectivity, the extent to which a manufacturer adopts and integrates Ind4 technologies, which is referred to as its IND4AL, can have a substantial impact on operational efficiency, particularly in competitive markets characterized by growing customer expectations (Zheng et al., 2021).

Specifically, it can be anticipated that companies with higher levels of Ind4 technology implementation will exhibit more efficient CMP, given that it enables them to better leverage real-time data, automation, and integrated digital systems to enhance responsiveness and personalization (Frank et al., 2019). Furthermore, a stronger adoption of Ind4 technologies may enhance the positive effect of CMP on financial performance. Based on this reasoning, we propose the following hypothesis:

Hypothesis 1a: IND4AL significantly and positively influences CMP.

Hypothesis 1b: IND4AL significantly moderates the relationship between CMP and CFP.

Likewise, it can be anticipated that companies with higher levels of Ind4 technology implementation may lead to better financial outcomes, given that it enables better operational efficiency and thus leads to better financial performance. We thus hypothesize:

Hypothesis 1c: IND4AL significantly and positively influences CFP.

Effective customer management enables companies to enhance customer satisfaction through timely service delivery, personalized engagement, and responsive problem resolution (Verhoef et al., 2010). It also helps firms retain customers, leading to repeat business and long-term loyalty (Badawi and Muafi, 2024). In addition, strong customer management reduces service errors and redundancies, thereby lowering costs and improving profit margins (Kumar and Reinartz, 2016). Notably, prior studies (e.g., Grönroos, 2004; Verhoef et al., 2010) have shown that companies emphasizing customer orientation often outperform their peers in key financial indicators such as revenue growth and return on assets. Based on this evidence, we hypothesize:

Hypothesis 2: CMP significantly and positively influences financial performance.

3. Methods

3.1 Participants

To test the proposed hypotheses, we employed a survey-based methodology. A total of 800 manufacturing companies were randomly selected from the Ministry of Economic Affairs' database, each either implementing or intending to implement Ind4 technologies. Of these, 220 companies consented to participate, and 108 provided fully completed questionnaires.

The survey consisted of two parts. The initial part collected demographic and organizational background through open-ended questions, capturing information such as the respondent's gender, years of professional experience, company size, and industry classification. The second part contained closed-ended items assessed using either a four-point or seven-point Likert scale.

Following the removal of incomplete responses, the final sample consisted of 91 manufacturing companies across 14 distinct sectors, including but not limited to chemicals, biotechnology, petrochemicals, automotive, textiles, food manufacturing, rubber products, optoelectronics, semiconductors, electrical and electronic systems, metallurgy, machinery, and construction materials.

3.2 Measures and Analysis

The constructs for Ind4AL, CMP, and CFP were developed based on a comprehensive review of prior research. Ind4AL was measured using a ten-item scale adapted from Agca et al. (2017). CMP was evaluated using a five-item scale adapted from Grigoroudis et al. (2012). CFP was measured using a five-item scale adapted from Chen (2018).

Furthermore, to control for the potential influence of company size on financial outcome, firm equity, indicating the capital dedicated to supporting operations, was incorporated as a control variable in the analysis.

The analysis of the proposed model was conducted in two stages. Initially, we performed confirmatory factor analysis (CFA) to validate the measurement model, following the procedures outlined by Chen (2018) and Harrington (2009).

Subsequently, structural equation modeling (SEM) with bootstrapping techniques, as suggested by Kline (2015), was employed to test the hypothesized relationships.

4. Results

The measurement model adopts a congeneric structure, where correlations exist among the latent constructs—Ind4AL, CMP, and CFP. The overall model demonstrates acceptable fit with the data. To be specific, the chi-square to degrees of freedom ratio is 1.60, which is well below the commonly accepted cutoff of 3. The model also performs well on other key fit indicators—IFI and CFI are both at 0.95, and TLI is at 0.93—all surpassing the recommended threshold of 0.90. In addition, the RMSEA is 0.08, suggesting a reasonably good fit between the model and the data (Harrington, 2009).

We conducted hypothesis testing by following the analytical procedure outlined in Chen (2021). Table 1 outlines the unstandardized path coefficients for the proposed moderated mediation model, which was tested using SEM with 5,000 bootstrap samples, following the guidance of Kline (2015). The model shows an excellent fit with the data, as reflected in the fit statistics: RMSEA is 0.01, the chi-square to degrees of freedom ratio is 0.54, and all other indices—TLI, IFI, and CFI—are at a perfect 1.00.

Table 1. Bootstrap-based structural unstandardized regression weights

Sources		Parameter estimates			
Dependent	Independent	<i>B</i>	Lower	Upper	<i>P</i>
CMP	Ind4AL	0.16	-0.12	0.42	0.2650
CMP	Ind4AL* CMP	0.19	0.01	0.33	0.0410
CFP	Ind4AL	0.05	-0.27	0.30	0.8490
CFP	CMP	0.67	0.42	0.92	0.0000
CFP	Equity	0.10	-0.09	0.31	0.2630
Chi-square/Degrees of freedom		0.54			
TLI		1.00			
IFI		1.00			
CFI		1.00			
RMSEA		0.01			

Note: The results are derived from 5,000 bootstrap resamples. In the results, *B* denotes the estimated unstandardized path coefficient, Lower and Upper represent the lower and upper bounds of the bias-corrected percentile 95% CI, respectively, and *P* indicates the statistical significance level.

As shown in the table, the unstandardized path coefficient representing the direct effect of Ind4AL on CMP is not statistically significant, suggesting that Ind4AL does not exert a direct influence on CMP. Further, the bias-corrected 95% confidence interval (CI) does not exclude zero, reinforcing the lack of statistical significance (Chen, 2021). Therefore, Hypothesis 1a, which posits a positive relationship between Ind4AL and CMP, is not supported. A similar conclusion is also drawn for Hypothesis 1c, as the direct effect of Ind4AL on CFP is not statistically significant, with the 95% confidence interval including zero. Therefore, Hypothesis 1c, which predicts a positive relationship between Ind4AL and CFP, is not supported.

The unstandardized coefficient for the interaction between Ind4AL and CMP is 0.19, reaching statistical significance at $P = 0.0410$. The bootstrapped bias-corrected 95% CI ranges from 0.01 to 0.33, excluding zero and thereby confirming the significance of the interaction effect. These results indicate that Ind4AL moderates the relationship between CMP and CFP, providing support for Hypothesis 2b.

As the table also shows, CMP has a strong and direct effect on CFP, with the unstandardized path coefficient being highly significant ($P < 0.001$). The 95% bias-corrected CI excludes zero, adding confidence to the reliability of this finding. Based on this, Hypothesis 2—stating that CMP positively influences CFP—is supported. Figure 2 presents the model framework along with standardized coefficients and provides a summary of the hypothesis testing outcomes.

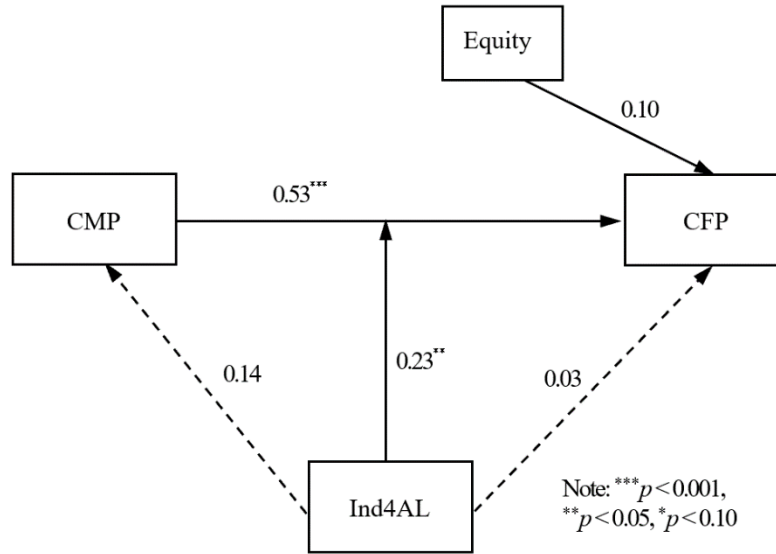


Figure 2. Bootstrap-Based SEM Results for Standardized Parameter Estimates with 1,000 Resamples

5. Discussion and Conclusion

Although much of the existing research on Ind4 focuses on technological advancements and operational efficiency, its impact on financial outcomes remains relatively unexplored. This study seeks to address that gap by proposing a model that examines the relationships among Ind4 implementation, customer management, and financial outcomes using bootstrap-based SEM with 5,000 resamples. The results show that CMP significantly and positively affects CFP, and Ind4AL positively moderates the CMP–CFP relationship. However, the direct effects of Ind4AL on CMP and CFP are not significant.

Our research results have two important implications. First, our findings suggest that Ind4AL does not directly influence CMP or CFP, but it enhances the effectiveness of CMP. This indicates that Ind4 technologies act more as enablers or amplifiers rather than direct performance drivers. A clear managerial implication is that managers should align their digital transformation strategies with customer-facing operations to fully unlock the benefits of Ind4.0 investment.

Second, our results reinforce the view that customer management capabilities are a key driver of financial performance, consistent with resource-based and market orientation theories. Another managerial implication is that merely adopting Ind4 technologies will not ensure improved financial outcomes. Their value is maximized when paired with strong customer management practices. Firms should implement digital tools in ways that directly support CMP to fully capitalize on the benefits of Industry 4.0 adoption.

As with any research, this study is subject to certain limitations. First, the analysis is based on a sample of 91 firms. Although we employed bootstrap-based methods to enhance the generalizability of our research findings (Chen, 2021; Kline, 2015), future research could further strengthen these results with larger samples.

Second, our study is based on cross-sectional data, and it doesn't fully capture how relationships may evolve over time. Future research could conduct longitudinal studies that help uncover time-lagged effects and offer deeper insights into the changing dynamics among the variables.

Acknowledgments

We gratefully acknowledge the support of the National Science and Technology Council of Taiwan, which made this research possible.

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Biography

Dr. Hong Long Chen, a former full professor at the National University of Tainan in Taiwan, is a clinical business faculty at the Anderson School of Management at the University of New Mexico. He is also a member of the Tau Beta

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