**Examining the Impact of Dynamic Capabilities on the Financial Performance of Manufacturing Companies**

**Abstract**

This study tries to empirically investigate the effect of dynamic capabilities on manufacturing companies' financial performance by concentrating on three main dimensions: integration, learning, and reconfiguration capabilities. By adopting a lower-order construct approach, this research work clarifies the direct impact of dynamic capabilities on the financial performance. The data from 216 manufacturing companies in Dakshina Kannada, Karnataka, India, were collected and Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for analysis. The results demonstrated that all three capabilities positively affect the financial performance of the manufacturing firms. Furthermore, the IPMA analysis indicated that reconfiguration capability is relatively more important but underperforms compared to integration and learning capabilities. The results of this study offer insights into the critical role of dynamic capabilities in advancing firm performance. Furthermore, it contributes to the present literature by confirming that dynamic Capabilities directly affect firms' performance when assessed as a lower-order construct.

**Keywords:** Dynamic Capabilities (DC), Integration Capability, Learning Capability, Reconfiguration Capability, Financial Performance, Manufacturing Companies.

1. **Introduction**

The business environment is changing rapidly and unpredictably, and business managers are more exposed to this dynamic environment in modern days (Adeoye et al., 2012). Increased competition, changes in customer preferences, and economic recessions disrupt business operations and require companies to remain adaptable (Acquaah et al., 2011). To remain competitive in constantly changing and complex business environments, manufacturing operations must adopt strategic, forward-looking approaches (Liu, 2013). Moreover, globalization introduces new technologies and exposes developing countries to even greater competition. As a result, SMEs must now compete not only with each other but also with larger manufacturing firms. To maintain their competitiveness, they should not only depend on incentives from the government; they must also adopt business practices according to the evolving market competition and advanced manufacturing technologies (Tuanmat & Smith, 2011). Based on the Resource-Based View (RBV), superior business performance attainment and long-term competitive edge depend on valuable, unique, rare, and non-interchangeable resources (Barney, 1991). In contrast, the Dynamic Capabilities (DC), as an expansion of RBV theory, focuses on the development and transformation of resources (Hong et al., 2018). DC refers to those capabilities of the companies that enable them to adapt according to the changes in the surrounding business environment (Yan et al., 2022; Laaksonen & Peltoniemi, 2018). As proposed by Teece et al. (1997), DC is the capability of the companies to learn, integrate, and reorganize resources inside and outside the organization based on business environment changes. Generally, scholars agree that organizational capabilities are a key contributor to the overall performance of firms (Drnevich & Kriauciunas, 2011). However, the debate persists in the literature regarding whether DC impacts performance directly or indirectly. Hernández-Linares et al. (2021) argued that DC is a lower-order construct and directly impacts firm performance in lower-order constructs, and those studies that have questioned the direct impact of DC have considered DC as higher order constructs. This study investigates the direct influence of DC as lower-order constructs on manufacturing companies’ financial performance by focusing on three dimensions: integration, learning, and reconfiguration capabilities. This research study contributes to the current literature addressing the existing ambiguity and clarifying the direct impact of DC as lower-order constructs on the manufacturing companies' financial performance.

1. **Literature Review and Hypothesis Development**

Mainly two kinds of organizational capabilities are there: operational capabilities, which denote regular processes, skills, and routines within operations management, and DC, which refer to those capabilities of the organization that enable them to adapt to the changes in environment changes (Yan et al., 2022; Laaksonen & Peltoniemi, 2018). For the first time, the DC concept was conceptualized by (Teece et al., 1997). DC enables business enterprises to develop, implement, and secure intangible resources to ensure their competitive advantage in the long-term (Teece, 2007). The DC theory, as a development of the RBV theory, focuses on the renewal and development of resources instead of the RBV theory, which emphasizes appropriate resource selection (Hong et al., 2018). These capabilities are grounded in the overall activities within the organization that restructure its way of operation and enable the firm to create considerable economic change (Fainshmidt et al., 2019). The management researchers widely agree that organizational capabilities are a vital contributor to the overall performance of the firms (Drnevich & Kriauciunas, 2011).

The DC concept has been extensively researched in the context of business (Zhou et al., 2017; Yan et al., 2022; Dejardin et al., 2023). Kareem & Kummitha (2020) studied DC in supply chains and its effect on the manufacturing companies’ operational performance and found that DC, such as collaboration, agility, and responsiveness, significantly improved operational performance. Another study performed by Yan et al. (2022) tested the effect of operational capabilities and DC on companies' performance and found that both operational and DC, directly and indirectly, impact the companies’ performance. Dejardin et al. (2023) revealed that DC positively affects SMEs' financial performance, measured by the turnover of the companies. Considering the valuable role of DC in superior performance, the full advantages of DC can be achieved under two conditions: an effective organizational structure and intense competition in the market (Wilden et al., 2013). Mohaghegh et al. (2021) studied the effect of DC on the sustainability of the companies. Eikelenboom & De Jong, (2019) looked into the DC effect on the SMEs’ environmental, economic, and social performance. Beske, (2012) discussed the incorporation of DC into supply chain management.

The present literature strongly supports the positive effect of DC on the organizations’ performance across various contexts. For example, an empirical analysis of the literature published in peer-reviewed journals by Pezeshkan et al. (2016), studied the extent of support from the literature on the link between DC, performance, and competitive advantage; their analysis showed 60% of the empirical studies support the positive outcome of DC on companies’ performance; in addition, the level of support was higher when performance was used as the dependent variable instead of competitive advantage (56%). However, there is a huge discussion on whether the DC directly or indirectly influences firm performance (Pundziene et al., 2021). Protogerou et al. (2012) highlighted that DC influences the companies' performance through the mediating role of two variables, namely marketing capability and technological capability, and the direct relationship is insignificant. Furthermore, Baía and Ferreira, (2024) noted that the indirect relationship is the most promising link between firm performance and DC. Alternatively, many research studies observed a positive direct connection between firm performance and DC. For example, Garrrido et al. (2020) investigated the direct effect of three aspects of DC (seizing, sensing, and reconfiguration) on performance, and the direct effect was supported. Zhou et al. (2017) studied the effect of three DC dimensions (seizing, sensing, and reconfiguration) on the companies’ financial performance directly and indirectly mediated by technological and market innovation and showed that sensing and reconfiguration but not integration have significant positive direct impacts on financial performance. According to Hernández-Linares et al. (2021) DC is often treated in the literature as a higher-order construct, and it is proposed that DC should be considered as a lower order construct, with each dimension potentially influencing firm performance individually rather than as a generic higher-order construct. Consistent with the above argument, Pavlou and El Sawy (2011) also mentioned that DC is a lower-order construct. Moreover, Studies that treated DC as lower-order constructs, such as Singh & Rao, (2017) and Dhaheri et al. (2023), found positive relationships. Moreover, Martins (2022) also highlighted the importance of lower dimensions of DC and found the positive direct influence of lower-order sub-elements of DC on the performance of the firms.

DC is considered a multidimensional construct (Dejardin et al., 2023). Multiple studies have investigated several aspects of DC such as integration, integration, reconfiguration (Farzaneh et al., 2022; Singh & Rao, 2017; Lin & Wu, 2014), sensing, seizing, reconfiguration (Wilden et al., 2013a), conceptualizing, sensing, scaling and stretching, coproducing and orchestrating, (Dejardin et al., 2023), collaboration, integration, agility, responsiveness (Kareem & Kummitha, 2020), sensing, coordination, seizing, reconfiguration, integration, and learning (Takahashi et al., 2017). Based on the literature, learning, integration, and reconfiguration capabilities were used as three main dimensions of DC (Farzaneh et al., 2022; Singh & Rao, 2017; Lin & Wu, 2014), and conceptualize the company’s ability to learn, integrate, and reconfigure the resources to adjust itself to the changes in the sternal business environment as DC of the company (Singh & Rao, 2017). This is according to Teece et al., (1997), as cited by Borch & Madsen, (2007), identifying learning, integration, and reconfiguration as three main organizational DC. Researchers, since the 1990s, have mentioned integration capability as a key element for performance improvement (Singh & Rao, 2017). Eikelenboom & De Jong (2019) argued that the environmental, social, and economic performance of companies is positively affected by integration capability. Learning capability functions like a mechanism for creating and converting knowledge into financially rewarding products and services (Luo, 2000), and enables the generation and expansion of competitive advantage for the company (Ferreira et al., 2021). Resource base reconfiguration is the ability of the company to rearrange the operation and resource capabilities (Yi, 2020; Wilden et al., 2013). The current literature on the connection between DC and organizational performance provides substantial evidence that the company’s reconfiguration capability contributes to improved performance (Singh & Rao, 2017). Earlier studies have identified reconfiguration capability as a key component of DC (Yi, 2020).

Considering the above literature review, there is enough theoretical and literature support for the development of these hypotheses.

**H1:** Integration capability positively impacts the financial performance of the manufacturing companies.

**H2:** Learning capability positively impacts the financial performance of the manufacturing companies.

**H2:** Reconfiguration capability positively impacts the financial performance of manufacturing companies.

1. **Methodology**
   1. **Sampling and Data**

The study employed a survey design and collected the data of the study from manufacturing firms in the Dakshina Kannada district of Karnataka, India. The District Industries Centre (DIC), Dakshina Kannada, provided a complete list of operating manufacturing companies in the district. Based on this official database, the aggregate number of manufacturing firms in the district was 381, comprised of 15 large-scale, 22 medium-scale, and 344 small-scale manufacturing companies. Due to the small number of large-scale and medium-scale companies, all the companies were surveyed. Regarding small-scale companies, the probability sampling method was employed. In the survey, a structured questionnaire was and physically distributed to the high-ranking managers of the companies across Dakshina Kannada. Each company was personally visited to distribute the questionnaire. This face-to-face approach facilitated the distribution process and ensured that respondents clearly understood the Questionnaire. In total, around 253 research questionnaires were distributed, and consequently, the data from 236 companies was collected. After data cleaning, 216 questionnaires were retained, comprised of 12 large-scale, 17 medium-scale, and 187 small-scale manufacturing companies, with a total response rate of 85.3%.

* 1. **Questionnaire Design and Measurement Scale**

For primary data collection, a structured questionnaire was used. It was designed to measure accurately the constructs in the study and includes learning, integration, and reconfiguration capabilities as three distinct aspects of DC and financial performance. The items for DC were adopted from earlier validated research papers (Farzaneh et al., 2022; Singh & Rao, 2017; Lin & Wu, 2014). The financial performance is measured using three key financial indicators, namely, return on investment, increase in sales of products, and increase in the company’s profit (Valdez-Juárez et al., 2024; Eslami et al., 2024). Statements of the questionnaire were responded to according to the Five-Point Likert scale where 5 represents ‘Strongly Agree’ and 1 represents ‘Strongly Disagree’. The adoption of previously tested scales ensures the measurement scale’s content validity and alignment with established research frameworks.

Table 1. *Measurement scale*

|  |  |  |
| --- | --- | --- |
| **Number** | **Constructs** | **Items** |
| 1 | Integration Capabilities | We consider customer information collection and potential market exploration |
| 2 | Our company utilizes the specialized services of other organizations in its management decisions. |
| 3 | Our company focuses on integrating industry-related technologies to develop new products. |
| 4 | We integrate historical methods and experiences in handling company issues. |
| 5 | Learning Capabilities | We have constant industry-related knowledge learning |
| 6 | We have frequent training programs within the organization |
| 7 | We have frequent knowledge sharing and establishment of learning groups |
| 8 | We have frequent cross-departmental training programs. |
| 9 | Reconfiguration Capabilities | Our company focuses on re-organizing jobs and positions when needed |
| 10 | Our company reacts quickly to market changes. |
| 11 | We have a rapid organizational response to competitors' actions. |
| 12 | We have effective and efficient communication with partner organizations |
| 17 | Financial Performance | Improvement in return on investment |
| 18 | Increase in sales of products |
| 19 | Increase in the profit of the company |

1. **Analysis and Results**

For data analysis, the study employed Partial Least Squares Structural Equation Modeling (PLS-SEM). As noted by Sarstedt et al.(2021), PLS-SEM is broadly acknowledged as an effective method for assessing path models containing latent variables and testing relationships among them. Hair et al. (2019) mentioned that PLS-SEM is increasingly applied in many disciplines of social science research. The first step of PLS-SEM analysis involves analysing PLS-SEM outcomes for the measurement model, in case of satisfying the necessary criteria, the following phase is of the structural model assessment (Hair et al., 2019).

* 1. **Measurement Model**

In reflective measurement model assessment, measures such as indicators loadings, Cronbach’s alpha and composite reliability for establishing internal consistency of the data, convergent validity measured by AVE, discriminant validity, and indicators multicollinearity (VIF) are used (Hair et al., 2019). Indicator loadings must be greater than 0.708, and Cronbach’s Alpha must be beyond 0.70, and also CR, while values greater than 0.95 show redundancy. Moreover, the AVE should not be less than 0.50 (Hair et al., 2019). The VIF, as an indicator of multicollinearity, is preferred to be below 3 (Hair et al., 2019). All items have outer loadings above the threshold value of 0.708 as presented in Table 2; hence, each item adequately represents its respective construct. Furthermore, all values of the VIF are less than 3 as recommended, indicating no multicollinearity among the indicators. Moreover, Cronbach’s alpha and CR values are above 0.70 benchmark value, and all AVE as a measure of convergent validity, are above 0.50; hence, the internal consistency of the study and convergent validity of the study are established (See Table 2)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Construct** | **Items** | **Outer Loading** | **VIF** | **Cronbach's alpha** | **CR** | **AVE** |
| Integration Capabilities | IC1 | 0.875 | 2.071 |  |  |  |
| IC2 | 0.827 | 1.919 |  |  |  |
| IC3 | 0.778 | 1.766 |  |  |  |
| IC4 | 0.852 | 2.122 | 0.855 | 0.901 | 0.695 |
| Leaning Capabilities | LC1 | 0.790 | 1.748 |  |  |  |
| LC2 | 0.795 | 1.783 |  |  |  |
| LC3 | 0.851 | 1.981 |  |  |  |
| LC4 | 0.824 | 1.84 | 0.832 | 0.888 | 0.665 |
| Reconfiguration  Capabilities | RC1 | 0.826 | 1.97 |  |  |  |
| RC2 | 0.903 | 2.795 |  |  |  |
| RC3 | 0.869 | 2.455 |  |  |  |
| RC4 | 0.819 | 1.954 | 0.877 | 0.916 | 0.731 |
| Financial Performance | FP1 | 0.816 | 1.501 |  |  |  |
| FP2 | 0.871 | 1.634 |  |  |  |
| FP3 | 0.730 | 1.342 | 0.734 | 0.848 | 0.652 |

Table 2: *Measurement model assessment*

The discriminant validity is established through the Heterotrait-Monotrait (HTMT) ratio, cross loadings, and Fornell and Larcker criterion. As stated by Henseler et al. (2015), the HTMT values must be lower than 0.85 or at least 0.9. Furthermore, according to the Fornell and Larcker criterion, for each latent variable, the square root of its AVE must be higher than its corelation with other constructs. Hence, the requirements for the discriminant validity of the study are met as per the HTMT ratio and Farnell and Larcker criteria, as shown in Table 3.

Table 3: *Heterotrait-Monotrait (HTMT) ratio and Fornell and Larcker Criterion*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Construct** | **FP** | **IC** | **LC** | **RC** |
| **FP** | 0.808 | ***0.771*** | 0.817 | 0.835 |
| **IC** | 0.637 | 0.834 | ***0.645*** | 0.704 |
| **LC** | 0.651 | 0.557 | 0.815 | ***0.799*** |
| **RC** | 0.679 | 0.622 | 0.684 | 0.855 |

Note: The bold and italicized diagonal numbers show the AVE’s square root, while the lower and upper diagonal numbers show construct correlations (Fornell-Larcker) and HTMT ratios, respectively

The cross-loadings analysis confirms discriminant validity by comparing each item’s outer loading on its related latent variable with any other latent variable. The cross-loadings analysis is presented in Table 4. It shows that all indicators load higher on their related constructs.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **FP** | **IC** | **LC** | **RC** |
| **FP1** | 0.816 | 0.576 | 0.506 | 0.504 |
| **FP2** | 0.871 | 0.570 | 0.619 | 0.648 |
| **FP3** | 0.730 | 0.372 | 0.433 | 0.476 |
| **IC1** | 0.653 | 0.875 | 0.559 | 0.614 |
| **IC2** | 0.506 | 0.827 | 0.464 | 0.514 |
| **IC3** | 0.397 | 0.778 | 0.400 | 0.448 |
| **IC4** | 0.517 | 0.852 | 0.407 | 0.470 |
| **LC1** | 0.488 | 0.394 | 0.790 | 0.521 |
| **LC2** | 0.471 | 0.420 | 0.795 | 0.539 |
| **LC3** | 0.590 | 0.514 | 0.851 | 0.583 |
| **LC4** | 0.562 | 0.477 | 0.824 | 0.583 |
| **RC1** | 0.562 | 0.530 | 0.514 | 0.826 |
| **RC2** | 0.657 | 0.618 | 0.619 | 0.903 |
| **RC3** | 0.557 | 0.501 | 0.591 | 0.869 |
| **RC4** | 0.535 | 0.465 | 0.614 | 0.819 |

Table 4: *Cross Loadings*

Note: IC: Integration Capability, LC: Learning Capability, RC: Reconfiguration Capability, FP: Financial Performance

* 1. **Structural Model**

Once the measurement model evaluation is done and ensured that all criteria are met, the examination of the structural model is conducted. Th Structural model concerns evaluating the relations between latent variables and establishes the overall model’s robustness (Hair et al., 2022). Firstly, the model’s explanatory and predictive power should be established, and finally, path coefficients significance is analysed to confirm or reject the hypothesized relationships (Chin, 1998).

Figure1: Graphical representation of the model

A diagram of a network

AI-generated content may be incorrect.

Source: *Output from the Smart PLS Software*

Both R2 (coefficient of determination) and f2 are measures of explanatory power. The analysis demonstrates an R² of 0.575 and indicates that 57.5% of the variance in the outcome variable (financial performance) is presented by the predictor variables. In addition, the f2(effect size) values for integration, learning, and reconfiguration capabilities were 0.114, 0.093, and 0.100, respectively.

The Stone-Geisser (Q²) criterion (Hair et al., 2019) and, according to (Liengaard et al., 2021), the Cross-Validated Predictive Ability Test (CVPAT) are measures for assessing the predictive power. In this model, the Q² value is 0.552 and indicates a substantial predictive power, and shows that the model can perfectly reproduce the same results when applied to new cases (Hair et al., 2019). Additionally, the CVPAT analysis reveals an average loss difference of -0.252 (t= 4.978, p = 0.000); therefore, the results from the PLS-SEM approach demonstrate that the predictive errors are significantly smaller compared to other models (Liengaard et al., 2021). Therefore, the predictive significance is confirmed. Lastly, the overall model fit is confirmed using the Standardized Root Mean Square Residual (SRMR) with a value of 0.068 below the benchmark value of 0.08 and demonstrates a sufficient fit between the model and the collected data.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Explanatory Power** | | | | | | | |
| **Predictors** | **Outcome** | | | **R Square** | **R Square Adjusted** | | **F Square** | |
| IC | FP | | | 0.575 | 0.569 | | 0.114 | |
| LC | 0.093 | |
| RC | 0.100 | |
| **Predictive Power** | | | | | | | |
| **Dependent Variable** | | | **Q-Square** | | | | |
| FP | | | 0.552 | | | | |
| **CVPAT Analysis** | | | | | | | |
|  | | **Average Loss Difference** | | **T-value** | | **P-value** | |
| FP | | -0.252 | | 4.978 | | 0.000 | |

Table 5: *Explanatory and predictive power*

Note: IC: Integration Capability, LC: Learning Capability, RC: Reconfiguration Capability, FP: Financial Performance

Finally, after the explanatory and predictive power assessment, the final component of the structural model includes hypothesis testing. The path coefficient from IC to FP is 0.292 (t=4.588, p=0.000). Consequently, the first hypothesis is confirmed and indicates that integration capability affects significantly financial performance. In the same way, the link between LC and FP is confirmed by a beta coefficient of 0.281 (t = 3.689, p = 0.000). Hence, the second hypothesis is also supported that the learning capability significantly and positively affects financial performance. Finally, the path coefficient from IC to FP is 0.306 (t = 3.602, p = 0.000) and confirms the last hypothesis that reconfiguration capability positively influences financial performance. In summary, all three hypotheses in the study were supported. It confirms the theoretical proposition that DC is vital for companies’ performance in a volatile business environment.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Hypotheses** | **Path coefficient** | **Standard deviation** | **T statistics** | **P values** | **Remark** |
| **H1: IC -> FP** | 0.292 | 0.063 | 4.588 | 0.000 | Supported |
| **H2: LC -> FP** | 0.281 | 0.076 | 3.689 | 0.000 | Supported |
| **H3: RC -> FP** | 0.306 | 0.085 | 3.602 | 0.000 | supported |

Table 6: *Hypotheses testing*

Note: IC: Integration Capability, LC: Learning Capability, RC: Reconfiguration Capability, FP: Financial Performance

* 1. **IPMA Analysis**

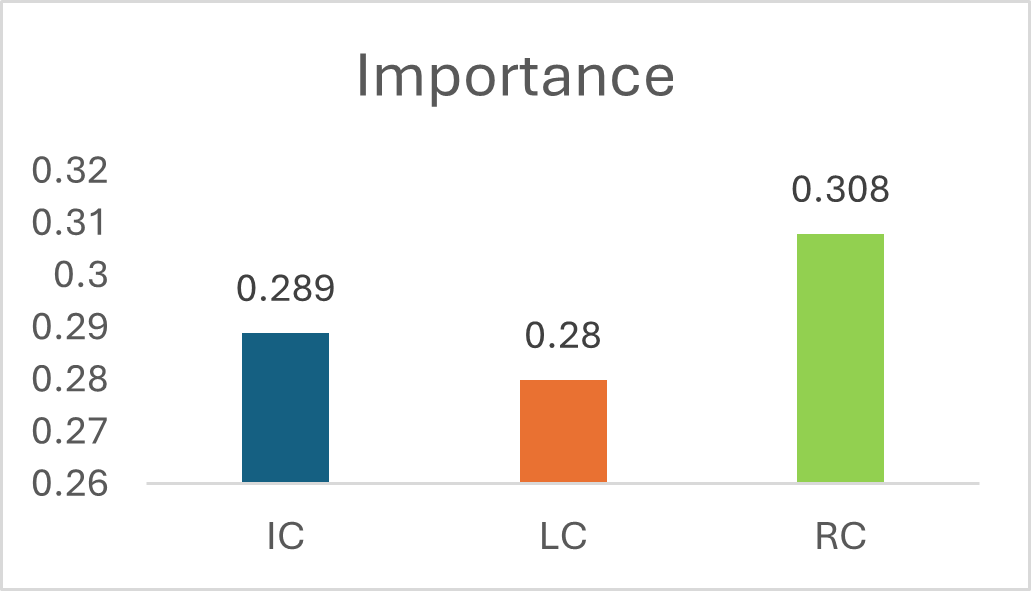
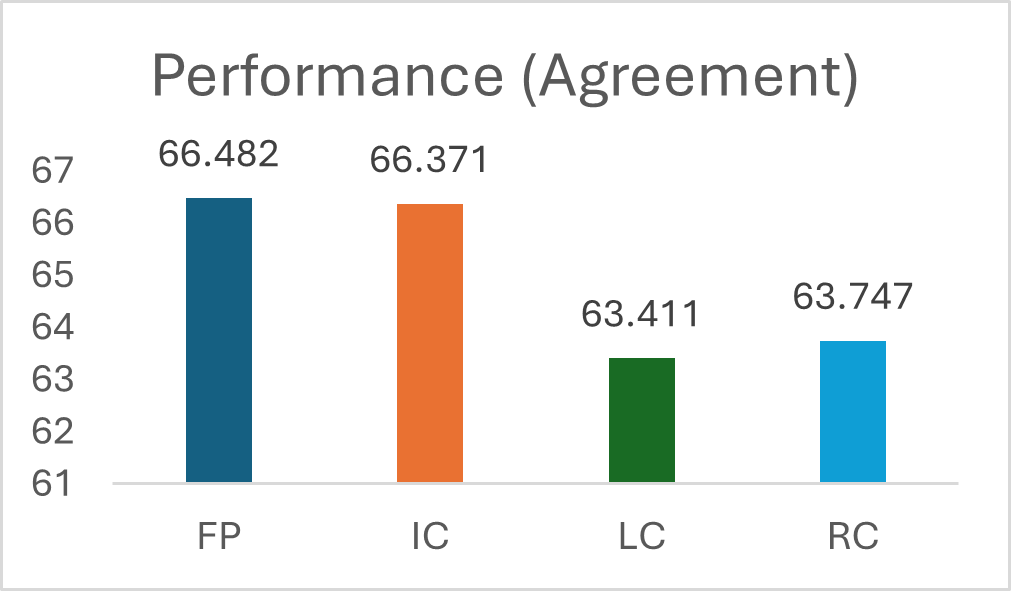
The Importance-Performance Map Analysis (IPMA) offers additional details about the model by combining the importance and performance of every latent variable of the study. IPMA analysis allows the researchers to gain additional findings and enrich their PLS-SEM analysis (Ringle & Sarstedt, 2016).This extends the results from the structural model and identifies the areas where companies are required to focus to improve their financial performance. In the IMPA analysis, the performance values represent the agreement level of respondents, while the importance values show the relative effect of each dynamic capability on the manufacturing companies' financial performance based on path coefficients. Table 7 presents the performance and the importance of latent variables of the study. Further, Figure 3 and Figure 4 represent graphically the importance and performance.

**Table 7** *IPMA Performance-Importance Analysis*

|  |  |  |
| --- | --- | --- |
| **Constructs** | **Performance (Agreement Level)** | **Importance (Path Coefficient)** |
| IC | 66.482 | 0.289 |
| LC | 66.371 | 0.280 |
| RC | 63.411 | 0.308 |
| FP | 63.747 |  |

Note: IC: Integration Capability, LC: Learning Capability, RC: Reconfiguration Capability, FP: Financial Performance

**Figure 2:** *Importance-Performance analysis Graphical representation*



*A graph with red circles and blue dots

AI-generated content may be incorrect.***Figure 3:** *Importance-Performance Map*

Source: *Output from Smart PLS software*

The results highlight that integration capability with a score of 66.482 has the highest performance followed closely by learning capability, which has a performance score of 66.371. Further, reconfiguration with the lowest performance score of 63.411 shows the highest importance in the model with a value of 0.308. This stresses the critical contribution of reconfiguration capability in improving the financial performance of the companies. These outcomes imply that although integration capability and leaning capability perform better; However, their importance is lower than reconfiguration capability in increasing financial performance. Ueberwimmer et al. (2018) also found that reconfiguration capability exerts the highest effect on financial performance. The second highly effective factor on financial performance was found to be integration capability. Therefore, learning capability has the lowest effect on financial performance in comparison to reconfiguration and integration capabilities.

1. **Discussion**

This study assessed the effect of integration, learning, and reconfiguration capabilities on the manufacturing companies' financial performance. It is widely discussed in the literature whether DC directly or indirectly impacts the company’s performance. Baía & Ferreira, (2024) and Protogerou et al. (2012) noted that there might not be a direct effect from DC on performance. Conversely, Garrrido et al. (2020), and Zhou et al. (2017) observed that DC directly affects firms’ performance. Hernández-Linares et al. (2021) argued that the reason behind this confusion in the literature about the direct impact is that DC is a lower-order construct, but it is treated in the literature as a higher-order construct. For instance, Wilden et al. (2013) examined the impact of DC as a higher-order construct and found an insignificant direct impact on firm performance. Interestingly, they highlighted that lower-order DC directly affects the performance of the companies. We tried to investigate DC as lower order constructs, including learning, integration, and reconfiguration capabilities, consistent with DC theory (Teece et al., 1997).

The first hypothesis was supported and showed that integration capability positively affects the companies’ financial performance. This supports the findings of Singh & Rao (2017), Yu et al. (2013). Integration capability positively influences financial performance, new capabilities, and marketing effectiveness (Jiang et al., 2015). Similarly, it was noticed that Learning Capability has a significant positive impact on the companies’ financial performance; hence, the second hypothesis was also supported. In line with this, Singh & Rao (2017) findings confirmed the positive effect of learning capability on companies’ financial performance. Further, this is proven that Learning capability positively affects manufacturing enterprises’ innovation performance and finally improves the competitive advantage (Chen et al., 2009). Ultimately, the third hypothesis of the study was also supported, and it was found that reconfiguration capability significantly impacts financial performance. In line with our finding, Tempelmayr et al. (2019), Zhou et al. (2017), and Shafia et al. (2016) confirm that reconfiguration capability positively impacts the performance of firms. The outcomes validate the theoretical propositions of DC theory (Teece et al., 1997) and reveal the key role of the ability of the companies to reconfigure and renovate the resource base in reaction to environmental changes (Teece, 2007). In addition, our PLS-SEM analysis confirms that our model reliably explains and predicts financial performance. In the model, the independent constructs explain 57.5% of the variance (R² = 0.575) and show strong predictive relevance (Q² = 0.552). The CVPAT analysis shows an average loss difference of 0.252 (t = 4.978, p= 0.000). Finally, the SRMR model fit value of 0.068 further supports the model’s goodness of fit. These results reinforce the legitimacy of our findings (Hair et al., 2017; Henseler et al., 2016; Shmueli et al., 2019)

The IPMA further clarifies the relative impact of these capabilities. In terms of importance, reconfiguration capability shows the greatest impact on the manufacturing companies' financial performance, succeeded by integration capability as the second highest important factor and, finally, learning capability. This is in agreement with the study of Ueberwimmer et al. (2018) suggesting reconfiguration capability as the most impactful capability. However, in terms of performance, it scored lower compared to integration capability and learning capability.

1. **Conclusion**

In this study, the effect of DC, namely integration, learning, and reconfiguration capabilities on the manufacturing companies' financial performance was analyzed employing the PLS-SEM method. The data from 216 manufacturing companies in Dakshina Kannada, Karnataka, India, were collected for the study. The results showed that all three dimensions positively impact financial performance. Further, it was revealed that there is a direct impact when a lower-order approach is applied in examining the impact of DC on the firm’s financial performance. These results support the DC theory (Teece et al., 1997) and stress that the companies need to develop these capabilities in reaction to the business ecosystem changes for achieving better performance.

1. **Limitations and Future Research recommendation**

There are certain limitations in this study. Since this study adopted a cross-sectional design, it restricts causal inferences. Moreover, the data of the data is self-reported, and it might introduce bias. Moreover, this study is focused specifically on the manufacturing sector, mostly small-scale companies located in the district of Dakshina Kannada, and this limits its generalizability. Future research may consider longitudinal approaches and examine these relationships across diverse industries and regions. This study examined the direct relationships in lower order; further studies may also examine mediating and moderating factors to offer a more inclusive understanding of their effects on performance.

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