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The Effect of Demand Forecasting on the Financial Performance of Manufacturing Companies in Cameroon

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Abstract

Purpose: This study examines the effect of demand forecasting on the financial performance of manufacturing companies in Cameroon.

Methodology: Adopting a cause-effect research design, data were collected through structured questionnaires from 223 manufacturing firms in the Littoral, Centre, and West regions. Structural Equation Modelling (SEM) using SPSS AMOS was employed to analyse the relationships. Demand forecasting was measured with five indicators, while financial performance was assessed using sales growth, net profit margin, and inventory turnover.

Findings: The results indicate a strong positive and statistically significant effect of demand forecasting on financial performance ($\beta = 0.633$, $p < 0.001$). The findings demonstrate that effective demand forecasting significantly reduces stock-outs, minimises excess inventory, optimises working capital, and enhances customer responsiveness.

Unique Contribution to Practice and Policy: The study contributes empirical evidence from a developing economy context and provides actionable recommendations for manufacturers and policymakers in line with Cameroon's Vision 2035 and National Development Strategy (NDS30).

Keywords: *Demand Forecasting, Financial Performance, Inventory Management Practices, Manufacturing Companies, Cameroon, Structural Equation Modelling*

1. Introduction

Strategic inventory management has emerged as a fundamental determinant of organisational performance in global manufacturing (Al Shukaili et al., 2025). Manufacturing firms increasingly treat inventory not as a static asset but as a dynamic resource whose management directly shapes cost structures, liquidity, and competitiveness. Among the various inventory management practices available to firms, demand forecasting occupies a foundational position because it determines how accurately a company can align production, procurement, and stock levels with actual market needs.

Demand forecasting is defined as the process of estimating future customer demand using historical sales data, market trends, and statistical or judgmental models (Chopra & Meindl, 2016). It allows firms to anticipate how much of a product to produce or order, when to order it, and how much safety stock to hold in order to avoid both shortages and costly overstocking (Goel et al., 2024; Aldahmani et al., 2024). Financial performance, on the other hand, refers to the extent to which a firm achieves its profitability, efficiency and growth objectives, and in this study is captured through three widely used indicators: sales growth (SG), net profit margin (NPM), and inventory turnover (INT) (Bîrcă, 2016; Olaniyan et al., 2020).

The relationship between the two constructs is not merely correlational but causal in nature. Accurate demand forecasting enables a firm to determine the right quantity and timing of production and procurement, which in turn minimises stock-outs and excess inventory, optimises the working capital tied up in stock, shortens the cash-conversion cycle, and improves customer responsiveness. These operational improvements translate directly into the financial outcomes of interest: fewer stock-outs sustain sales growth, lower holding and obsolescence costs improve net profit margin, and better-timed replenishment raises inventory turnover. Where forecasting is poor, the opposite occurs: firms either over-invest capital in inventory that generates no sales or under-invest and lose sales opportunities, both of which erode financial performance (Cannon, 2008; Koumanakos, 2008).

This interconnection is especially significant in the Cameroonian manufacturing context. Inventory constitutes between 40% and 60% of the total current assets of manufacturing firms (World Bank, 2020), meaning that decisions about how much stock to hold, decisions that are only as good as the forecast that informs them, have an outsized effect on firm liquidity and profitability. The manufacturing sector is also central to the government's industrialisation agenda under Vision 2035 and the National Development Strategy 2020-2030 (NDS30), which targets an increase in Manufacturing Value Added (MVA) from 14.5% to 25% of GDP (Republic of Cameroon, 2020). Achieving this target depends, in part, on manufacturing firms being able to convert their assets, inventory chief among them, into profitable output rather than allowing capital to remain tied up in unsold or obsolete stock.

Despite this recognised importance, many manufacturing companies in Cameroon continue to rely on rudimentary or intuition-based approaches to estimating demand rather than structured, data-driven forecasting systems. This has resulted in frequent stock-outs, excess inventory, high holding costs, and lost sales (Owajege & Saif, 2025; Akinlabi & Sonko, 2020; Teno et al., 2017). These operational failures are compounded by a volatile business environment characterised by unreliable electricity supply, congested ports, unpredictable lead times for imported raw materials, and fluctuating exchange rates, all of which increase the uncertainty that demand forecasting is meant to manage (Kuteyi & Winkler, 2022; Kanyepe et al., 2025).

It is against this background that the present study specifically analyses the effect of demand forecasting on the financial performance of manufacturing companies in Cameroon, measured by sales growth (SG), net profit margin (NPM), and inventory turnover (INT). By using demand forecasting as an inventory management practice and testing its effect using Structural Equation Modelling (SEM), a technique yet to be widely applied to this specific relationship in the Cameroonian manufacturing sector, the study seeks to provide localised, methodologically rigorous evidence to inform both managerial practice and the policy objectives of Vision 2035 and NDS30.

1.1 Statement of the Problem

Manufacturing is widely regarded as the backbone of structural transformation and economic resilience, and the Cameroonian government has placed industrialisation at the centre of its Vision 2035 and the National Development Strategy 2020-2030 (NDS30), which targets raising Manufacturing Value Added (MVA) from 14.5% to 25% of GDP by 2030 (Republic of Cameroon, 2020). However, the path toward this industrial ambition is obstructed by persistent operational inefficiencies in the management of current assets. Inventory, which typically constitutes between 40% and 60% of a manufacturing company's total assets, remains a source of massive capital leakage rather than a driver of value (World Bank, 2020).

In practice, this capital leakage is closely tied to poor demand forecasting. Manufacturing companies in industrial hubs such as Douala and Yaoundé frequently hold surplus stock because production and procurement decisions are not informed by reliable estimates of future demand, resulting in high storage costs and the eventual write-down of obsolete materials (Agu et al., 2016). At the same time, inadequate anticipation of demand leads to frequent stock-outs, causing production delays, lost sales, and erosion of market share (Akinlabi & Sonko, 2020). Many small and medium-sized manufacturing enterprises still rely on rudimentary, non-computerised methods of estimating demand, which increases the margin of error in production planning and inventory reconciliation (Kanyepe et al., 2025).

These forecasting failures are not solely a matter of internal company policy; they are compounded by a volatile business environment. Poor road networks, congested port operations, and unreliable electricity supply create unpredictable lead times that undermine the accuracy of demand plans,

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while fluctuating exchange rates and the high cost of importing raw materials increase the financial cost of forecasting errors (Kuteyi & Winkler, 2022; Kanyepe et al., 2025). In such conditions, a stock-out or an overstock resulting from poor demand estimation carries a heavier financial penalty than it would in a more stable operating environment, yet manufacturing firms rarely have the technological capability to manage this uncertainty through real-time data analytics.

While global studies have established a positive relationship between demand forecasting and firm financial performance (Cannon, 2008; Koumanakos, 2008), and while recent studies in Cameroon and neighbouring countries have examined inventory-related practices among SMEs (Owajege & Saif, 2025; Teno et al., 2017; Muffee, 2021), rigorous empirical evidence isolating the specific effect of demand forecasting on the financial performance of manufacturing companies in Cameroon remains scarce. Existing Cameroonian studies have tended to examine inventory management broadly, to focus on non-manufacturing SMEs, or to rely on descriptive statistics and simple regression rather than advanced multivariate techniques such as Structural Equation Modelling (SEM), which can more robustly capture the latent, multidimensional nature of both demand forecasting and financial performance.

This gap matters because, without localised and methodologically rigorous evidence on how demand forecasting affects financial outcomes, manufacturing managers lack a clear empirical basis for prioritising investment in forecasting systems, and policymakers lack the evidence needed to design targeted capacity-building support. Left unaddressed, the continued reliance on poor demand forecasting will keep manufacturing capital locked in unproductive inventory, undermining firm profitability and, by extension, the industrial transformation goals of Vision 2035 and NDS30. It is this problem, the inability of manufacturing companies in Cameroon to convert their demand forecasting practices into measurable financial gains, that the present study seeks to address.

1.2 Research Objective

The objective of this article is to analyse the effect of the usage of demand forecasting on the financial performance of manufacturing companies in Cameroon.

1.3 Hypothesis

H_{01}: Usage of demand forecasting has no significant effect on the financial performance of manufacturing companies in Cameroon.

2. Literature Review

2.1 Conceptual Literature

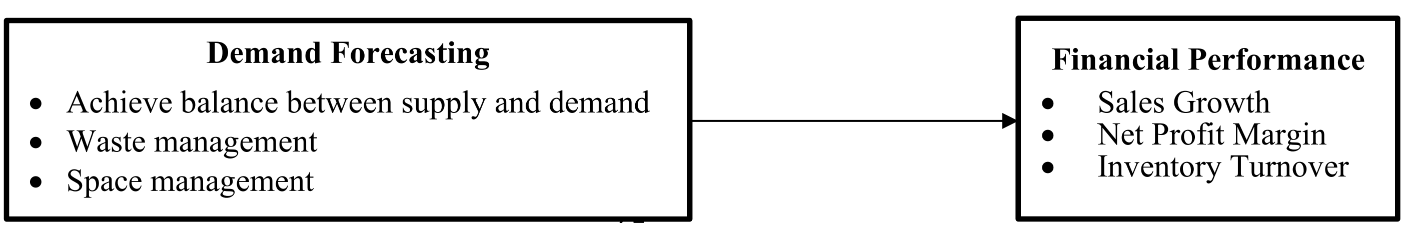

Figure 1: Conceptual framework

Source: Forsuh (2026)

Demand forecasting involves predicting future demand to support inventory and production decisions (Chopra & Meindl, 2016; Goel et al., 2024). Accurate forecasting helps minimise stock-outs and excess inventory, thereby optimising working capital and improving customer satisfaction (Aldahmani et al., 2024).

Financial performance is typically measured using profitability and efficiency indicators such as sales growth, net profit margin, and inventory turnover (Bîrcă, 2016; Olaniyan et al., 2020).

2.2 Theoretical Framework

This study is grounded in three complementary theories, Lean Theory, Stochastic Inventory Theory, and the Resource-Based View, each of which offers a distinct lens for explaining why and how demand forecasting influences the financial performance of manufacturing companies.

Lean Theory, also referred to as Lean Thinking, was popularised by Womack and Jones (1996) in their work Lean Thinking: Banish Waste and Create Wealth in Your Corporation, building on the Toyota Production System earlier documented by Womack et al. (1990). The theory holds that organisations should focus relentlessly on creating value for the customer while systematically eliminating waste, of which excess inventory is considered one of the most damaging forms because it ties up capital, incurs holding and obsolescence costs, and conceals underlying production problems (Womack & Jones, 1996). Central to Lean Theory is the idea that production should be pulled by actual customer demand rather than pushed on the basis of speculative forecasts, a principle that places accurate demand forecasting at the heart of waste reduction (Spear & Bowen, 1999).

Critics of Lean Theory argue that its emphasis on minimal inventory can be difficult to sustain in environments characterised by unreliable supply and infrastructure, such as much of Sub-Saharan Africa, where a near-zero-inventory posture may expose firms to stock-outs rather than protect them from waste (Hopp & Spearman, 2004). Others note that an overly narrow focus on cost-cutting can come at the expense of flexibility or employee welfare if not carefully balanced.

Lean Theory is relevant to this study because it explains the mechanism through which demand forecasting is expected to affect financial performance: by enabling firms to align production more closely with actual demand, accurate forecasting reduces the excess inventory that Lean Theory identifies as waste, thereby lowering holding costs, reducing capital tied up in stock, and improving profitability and liquidity indicators such as net profit margin and inventory turnover (Fullerton et al., 2013). In the Cameroonian manufacturing context, where infrastructural deficits often push firms toward high inventory buffers as a coping mechanism, Lean Theory provides the justification for why improved forecasting, rather than simply holding more stock, should be the more sustainable route to better financial performance.

Stochastic Inventory Theory addresses inventory decision-making under conditions of demand and lead-time uncertainty. Its foundations trace to Arrow et al. (1951), who introduced the classic newsvendor model for balancing the costs of overstocking against understocking under uncertain demand, with later syntheses by Hadley and Whitin (1963) and Porteus (2002) extending the framework to multi-period and reorder-point models. Unlike deterministic approaches that assume demand is known and constant, stochastic models treat demand as a random variable following a probability distribution and seek inventory policies that minimise expected costs, comprising ordering, holding, and shortage costs, while maintaining acceptable service levels (Porteus, 1988).

A recognised limitation of the theory is that it can become computationally demanding, particularly where demand is non-stationary, and it requires reasonably accurate estimation of probability distributions, an assumption that is difficult to satisfy in data-scarce environments such as many Cameroonian manufacturing firms (Silver et al., 2017).

This theory is directly relevant to the present study because Cameroonian manufacturing firms operate in an environment of considerable demand uncertainty driven by economic volatility, seasonality, infrastructural bottlenecks, and external shocks (World Bank, 2016; Republic of Cameroon, 2020). Stochastic Inventory Theory supplies the logic for why probabilistic, data-informed demand forecasting, rather than simple guesswork, is necessary to determine appropriate safety stock and reorder decisions, and why firms that forecast more accurately under uncertainty are better placed to avoid the costly extremes of stock-outs and overstocking that erode financial performance (Ma, 2019; Jeganathan et al., 2022).

The Resource-Based View (RBV), developed by Wernerfelt (1984) and formalised by Barney (1991), holds that firms achieve sustained competitive advantage by possessing resources and capabilities that are valuable, rare, inimitable, and non-substitutable (the VRIN criteria). Resources may be tangible, such as plant and inventory, or intangible, such as knowledge and organisational routines, with intangible resources generally more likely to satisfy the VRIN criteria because they are harder for competitors to imitate (Barney, 1991).

RBV has been criticised for being somewhat static, for offering limited guidance on how valuable resources are developed over time (an issue later addressed by the dynamic capabilities extension), and for risking circular reasoning if valuable resources are simply defined as whatever produces superior performance (Priem & Butler, 2001).

RBV is relevant to this study because it frames demand forecasting not merely as an operational routine but as a strategic capability. When a firm develops a superior demand forecasting capability, one that is difficult for competitors to replicate because it depends on accumulated data, systems, and staff expertise, this capability becomes a source of sustained competitive advantage that translates into superior financial performance (Barney, 1991). In the Cameroonian manufacturing sector, where firms face common external constraints such as infrastructural deficits and supply uncertainty, RBV suggests that competitive advantage, and by extension superior financial performance, will accrue to those firms that invest in and develop stronger internal forecasting capabilities rather than relying solely on external conditions.

2.3 Empirical Literature

At the global level, several studies confirm a positive relationship between demand forecasting and firm performance using varied methodologies. Goel et al. (2024), employing a systematic and holistic investigation of demand forecasting practices in supply chain management, found that firms adopting structured, data-driven forecasting approaches consistently reported improved operational efficiency and profitability compared with those relying on informal estimation methods. Aldahmani et al. (2024), using a uni-regression deep approximate forecasting model applied to supply chain data, demonstrated that advanced forecasting techniques significantly reduce forecast error and, consequently, the costs associated with both stock-outs and overstocking.

In Kenya, Maria and Odari (2025) examined the effect of demand forecasting practices on the performance of 54 small and medium-sized enterprises in Kajiado County using a descriptive survey design. Descriptive results showed that 84.5% of the sampled firms used demand forecasting, combining qualitative methods such as customer feedback with quantitative methods such as historical sales trend analysis, with an overall practice mean of 4.28 on a five-point scale. Regression analysis confirmed that demand forecasting had a statistically significant positive effect on firm performance ($\beta = 0.574$, $p < 0.05$), with the authors concluding that effective forecasting enhances sales, reduces inventory losses, and improves overall profitability.

Similar evidence emerges from other African contexts. Atnafu and Balda (2018), studying 188 micro and small manufacturing enterprises in the Arsi Zone of Ethiopia using Structural Equation Modelling, found that inventory management practices, including demand forecasting, had a significant positive direct effect on both competitive advantage ($\beta = 0.594$, $p < 0.01$) and organisational performance ($\beta = 0.438$, $p < 0.01$). In Kenya, Bosibori and Okibo (2015), using a case study design with 38 respondents, found that demand forecasting and related inventory categorisation practices had a moderate but significant influence on the operational performance of a county government enterprise, while Mulumba (2016), studying 65 agro-chemical manufacturing firms, found that forecasting, alongside just-in-time and vendor-managed inventory practices, explained a smaller but still positive share ($R^2 = 11.6\%$) of the variance in financial performance.

Within Cameroon specifically, Owajege and Saif (2025) surveyed 120 SME managers in Douala and, using descriptive statistics and regression models, found that structured inventory planning practices, of which forecasting-related techniques formed a part, were significant predictors of reported SME performance. Teno et al. (2017), examining small-scale cosmetics enterprises in Douala, found that planning-related practices, including lead-time management and stock classification, collectively explained 68% of the variance in cost performance. Muffee (2021), studying pharmaceutical shops in the Buea municipality using linear regression, found that inventory planning had a positive and significant effect on financial performance ($\beta = 0.283$, $p = 0.016$). While informative, none of these Cameroonian studies isolate demand forecasting as a distinct construct, nor do they apply Structural Equation Modelling, which limits the extent to which their findings can be generalised to the specific relationship examined in the present study.

Taken together, this body of literature demonstrates a broadly consistent positive relationship between demand forecasting and firm performance across global, African, and Cameroonian settings, but it also reveals important limitations. Methodologically, studies have relied predominantly on descriptive statistics and ordinary least squares regression, which do not adequately model demand forecasting as a latent, multi-item construct or account for measurement error, in contrast to Structural Equation Modelling, which permits simultaneous testing of both the measurement and structural relationships (Hair et al., 2019). Contextually, existing Cameroonian evidence is concentrated in SMEs and non-manufacturing sectors such as pharmaceutical retail and cosmetics, leaving medium-to-large manufacturing firms in the country's key industrial regions, Littoral, Centre, and West, comparatively under-researched. Substantively, most studies treat demand forecasting as one item within a broader inventory management bundle rather than isolating its specific, independent effect on financial performance. These gaps collectively justify the present study's use of Structural Equation Modelling to examine, in a previously under-studied manufacturing population, the isolated effect of demand forecasting on financial performance as measured by sales growth, net profit margin, and inventory turnover.

3. Methodology

3.1 Research Design

The study adopted a cause-effect (explanatory) quantitative research design (Creswell, 2008) as it is suitable to account for changes caused in one variable by another.

3.2 Study Area and Population

The study covered manufacturing companies in the Littoral, Centre, and West regions of Cameroon, as they represent the regions with the bulk of manufacturing activities within the country. The target population comprised all manufacturing companies registered with a legal form of Société Anonyme (SA) or Société à Responsabilité Limitée (SARL) operating in these three regions. According to the Directorate General of Taxation (DGI, 2023), there were 647 such manufacturing companies across the three regions, distributed as 506 companies in the Littoral region, 121 companies in the Centre region, and 20 companies in the West region. This population of 647 manufacturing companies constitutes approximately 70% of the 922 manufacturing companies with SA or SARL legal status registered in Cameroon and includes manufacturing companies of all categories operating in the country, providing an adequately representative frame for the study.

3.3 Sample Size and Sampling Technique

A sample of 223 manufacturing companies was selected from the target population of 647 companies using a combination of purposive (non-probability) sampling, to select the Littoral, Centre and West regions on the basis of accessibility and the concentration of manufacturing activity, and simple random sampling (probability sampling), to select individual manufacturing companies within each region (Cochran, 1977; Adwok, 2015).

The minimum required sample size was first computed using the Yamane (1967) formula, $n = N / [1 + N(e)^2]$, where n is the sample size, N is the population size, and e is the accepted margin of error (10%). Applying this formula by region yielded a minimum of 87 companies from the Littoral region (N = 506), 55 companies from the Centre region (N = 121), and 17 companies from the West region (N = 20), giving a minimum required sample of 159 manufacturing companies. Consistent with Cochran's (1977) recommendation that researchers over-sample to ensure a sufficient number of usable returns, and Hair et al.'s (2019) guidance that larger samples yield more stable parameter estimates for Structural Equation Modelling, the study surveyed beyond this minimum threshold and obtained 223 usable responses from manufacturing companies across the Littoral, Centre and West regions, exceeding the minimum requirement and strengthening the robustness of the SEM estimates reported in this study.

3.4 Data Collection Instrument

Primary data were collected using a structured questionnaire with five-point Likert scales. The instrument showed strong content and face validity (Muffee, 2021) and good reliability (composite reliability> 0.70).

3.5 Operationalisation of Variables

Demand Forecasting (DF): Measured with five items focusing on the use of formal systems, historical data, market trends, and seasonal adjustments.

Financial Performance (FP): A second-order latent construct comprising sales growth, net profit margin, and inventory turnover (Bîrcă, 2016).

3.6 Data Analysis

Data were analysed using Structural Equation Modelling (SEM) in SPSS AMOS version 23 (Byrne, 2016; Hair et al., 2019). Model fit was evaluated using CMIN/DF, CFI, TLI, RMSEA, and other indices. Assumptions of normality, multicollinearity, and linearity were tested and satisfied.

4. RESULTS

4.1 Measurement Model

Table 1: Measurement model fit indices

Fit Indices	Recommended Value	Source	Obtained Value
CMIN/df	<3	Kline (2016)	1.406
GFI	>0.90	Hair et al. (2010)	0.974
CFI	>0.90	Bentler (1990)	0.994
TLI	>0.90	Bentler (1990)	0.990
SRMR	<0.80	Hu and Bentler (1998)	0.028
RMSEA	<0.80	Hu and Bentler (1998)	0.043

Source: Forsuh (2026)

The measurement model demonstrated excellent fit as all values fall above and below the recommended values as

Table 2: Composite reliability coefficients

Construct	Item	Factor Loading	CR	AVE
Demand forecasting	DF1	0.75	0.885	0.608
	DF2	0.68		
	DF3	0.77		
	DF4	0.74		
	DF5	0.80		
Financial performance	SG	0.94	0.923	0.779
	NPM	0.85		
	INT	0.88		

Source: Forsuh (2026)

Table 2 presents the composite reliability (CR) coefficients for the construct in the model demand forecasting (DF) and financial performance (FP) which are all above 0.70 except DF2 suggesting high internal reliability. All average variance expected values shown in the table 2 are above 0.5, which suggest items are able to explain the variance in the construct

Table 3: Discriminant validity

	DF	FP
DF	0.750	
FP	0.460	0.894

Source: Forsuh (2026)

The discriminant validity is achieved, as the diagonal value are higher than the value in the respective matrix

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4.2 Structural Model

Table 4: Measurement model fit indices

Fit Indices	Recommended Value	Source	Obtained Value
CMIN/df	<3	Kline (2016)	1.979
GFI	>0.90	Hair et al. (2010)	0.941
CFI	>0.90	Bentler (1990)	0.973
TLI	>0.90	Bentler (1990)	0.959
SRMR	<0.80	Hu and Bentler (1998)	0.033
RMSEA	<0.80	Hu and Bentler (1998)	0.066

Source: Forsuh (2026)

The structural model showed good fit indices as all values fall above and below the various recommended values as shown by table 4 above.

4.2 Hypothesis Testing:

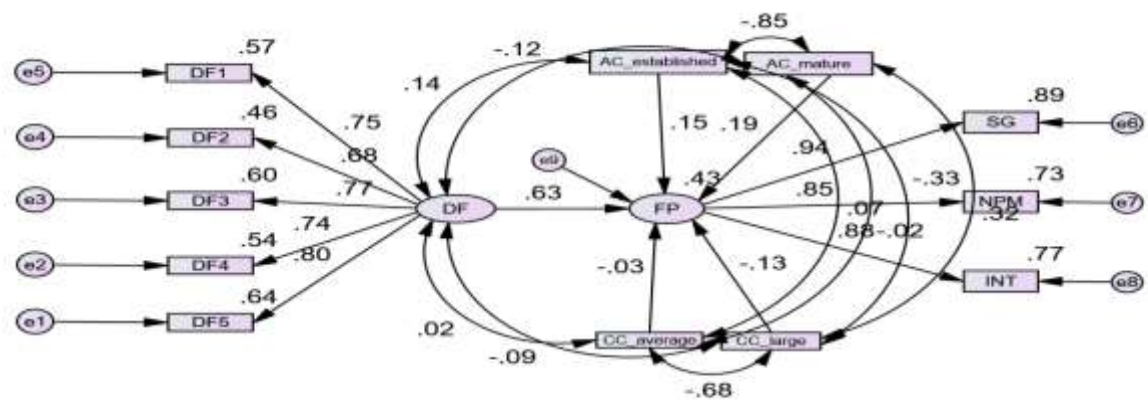

Figure 1: Standardised path coefficient between constructs

Source: Forsuh (2026)

Figure 1 shows standardised path coefficients between the constructs as well as the coefficient of determination (R-square) of 0.43. This implies that the contribution of demand forecasting in estimating financial performance is 43%.

Table 5: The regression weights and path coefficients

Path	Estimate (β)	SE	CR	P-value
DF →FP	0.633	0.084	8.720	***
AC_established →FP	0.147	0.132	1.361	0.837
AC_mature →FP	0.188	0.120	1.725	0.085
CC_average →FP	-0.033	0.088	-0.411	0.681
CC_large →FP	-0.130	0.079	-1.534	0.125

Source: Forsuh (2026)

The results in table 5 above shows that demand forecasting has a strong positive and highly significant effect on financial performance ($\beta = 0.633$, C.R. = 8.720, $p < 0.001$). This leads to the rejection of the null hypothesis H_{01}. As manufacturing companies increase their usage of demand forecasting, they will experience a positive increase in their financial performance.

Control variables (firm age and capital) showed relatively weak effects. Manufacturing companies of the age category, tend to perform better ($\beta = 0.188$, $p<.0.1$) financially compared to those of the young category. The model explained a substantial portion (43%) of variance in financial performance of manufacturing companies.

5. DISCUSSION

The results reveal a strong, positive, and statistically significant direct effect of demand forecasting on the financial performance of manufacturing companies in Cameroon ($\beta = 0.633$, $p < 0.001$), leading to the rejection of the null hypothesis H_{01}. Substantively, this indicates that manufacturing companies that make greater use of formal, data-driven demand forecasting, drawing on historical sales data, market trends, and seasonal adjustments, are better able to align production and procurement with actual market needs. This alignment reduces the incidence of stock-outs that erode sales growth, lowers the holding and obsolescence costs that depress net profit margin, and improves the timing of stock replenishment that underlies inventory turnover. In other words, demand forecasting affects financial performance not directly but through its effect on the operational efficiency of inventory decisions, consistent with the theoretical mechanisms outlined in section 2.2.

This finding is consistent with global evidence. Goel et al. (2024) and Aldahmani et al. (2024) similarly found that structured, data-driven forecasting approaches improve operational efficiency and reduce the costs associated with forecast error. However, the magnitude of the effect observed in this study ($\beta = 0.633$) is considerably larger than the $\beta = 0.574$ reported by Maria and Odari (2025) among Kenyan SMEs, suggesting that the effect of demand forecasting on financial performance may be more pronounced among the medium-to-large manufacturing companies sampled in this study than among the smaller enterprises typically examined in prior African research. This difference may reflect the greater capacity of larger manufacturing firms to invest in more sophisticated forecasting systems and to translate improved forecasts into measurable financial gains.

At the Cameroonian level, the result echoes the positive relationships reported by Owajege and Saif (2025) and Teno et al. (2017) between structured planning practices and firm performance in Douala. However, unlike these earlier studies, which relied on descriptive statistics or ordinary least squares regression and examined inventory practices as a broad bundle, the present study isolates demand forecasting as a distinct latent construct and applies Structural Equation Modelling, providing a more precise and methodologically robust estimate of its specific contribution, an effect size (43% of variance explained) that had not previously been quantified for demand forecasting alone within Cameroon's manufacturing sector. This suggests that the strength of the demand forecasting-financial performance relationship identified in earlier, less rigorous Cameroonian studies may, if anything, have been understated.

The strength of this relationship is particularly noteworthy given Cameroon's volatile business environment, characterised by unreliable electricity supply, congested port operations, and unpredictable lead times for imported raw materials (Kuteyi & Winkler, 2022). In such an environment, effective demand forecasting appears to play an amplified role: by helping manufacturers anticipate demand despite these external uncertainties, forecasting enables firms to minimise the safety stock and buffer inventory that would otherwise be needed to guard against supply disruptions, thereby freeing up working capital, reducing holding costs, and improving liquidity, effects that are directly reflected in the net profit margin and inventory turnover indicators used in this study.

These results strongly support Lean Theory (Womack & Jones, 1996) by demonstrating that improved forecasting reduces the excess inventory that the theory identifies as waste; Stochastic Inventory Theory (Porteus, 2002) by confirming that structured, probabilistic approaches to demand estimation help firms manage the demand uncertainty prevalent in the Cameroonian manufacturing environment; and the Resource-Based View (Barney, 1991) by illustrating how demand forecasting, when developed as a firm-specific capability, functions as a valuable and difficult-to-imitate resource capable of generating a sustained improvement in financial performance.

6. Conclusion

This study set out to examine the effect of demand forecasting on the financial performance of manufacturing companies in Cameroon, focusing specifically on sales growth, net profit margin, and inventory turnover as indicators of financial performance. Using a cause-effect research design, primary data were collected from 223 manufacturing companies operating in the Littoral, Centre and West regions of Cameroon and analysed using Structural Equation Modelling.

The findings show that the usage of demand forecasting has a strong, positive, and significant effect on the financial performance of manufacturing companies in Cameroon. Companies that rely more heavily on structured, data-driven approaches to estimating future demand experience fewer stock-outs, hold less excess inventory, make more efficient use of their working capital, and respond more effectively to customer needs, all of which translate into improved sales growth, higher net profit margins, and more efficient inventory turnover. The study also finds that firm characteristics such as age and capital base play only a secondary role compared with the central contribution of demand forecasting itself.

Overall, the study concludes that demand forecasting is not a peripheral operational task but a strategic capability that manufacturing companies in Cameroon must actively invest in and continuously improve if they are to strengthen their financial performance and contribute

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meaningfully to the country's broader industrialisation objectives under Vision 2035 and the National Development Strategy (NDS30). The evidence presented here offers manufacturers, and the policymakers who support them, a localised and empirically grounded basis for prioritising investment in demand forecasting capability as a route to more resilient and profitable manufacturing enterprises.

7. Recommendations

Based on the findings of this study, the following recommendations are proposed for practice, policy, and theory.

Practical Implications

Manufacturing companies in Cameroon should invest in structured, data-driven demand forecasting systems, moving beyond intuition-based estimation to techniques that incorporate historical sales data, market trends, seasonal adjustments and, where feasible, AI-enhanced forecasting tools. Given the strong effect of demand forecasting on financial performance identified in this study, firms should treat forecasting accuracy as a core determinant of profitability rather than a purely operational or administrative task, and should build the internal capacity, systems and data infrastructure needed to support it.

Policy Implications

Government agencies, particularly the Ministry of Industry, Mines and Technological Development, should support manufacturing companies through targeted capacity-building programmes, subsidies for forecasting software, and training initiatives that build technical demand-forecasting skills among manufacturing personnel. Given the amplifying effect of Cameroon's volatile business environment on the consequences of poor forecasting, continued investment in infrastructure, such as port efficiency and electricity reliability, would also reduce the external uncertainty that demand forecasting must contend with, thereby reinforcing the returns to improved forecasting practice. These interventions would directly support the industrialisation objectives of Vision 2035 and the National Development Strategy (NDS30) by helping manufacturing companies convert a larger share of their assets into productive, profit-generating output.

Theoretical Implications

This study extends Lean Theory, Stochastic Inventory Theory, and the Resource-Based View by providing empirical confirmation, using Structural Equation Modelling, that demand forecasting functions as the mechanism through which these theoretical propositions, waste reduction, uncertainty management, and strategic capability, translate into measurable financial outcomes in a developing-economy manufacturing context. Future theoretical work could build on these findings by examining demand forecasting alongside other inventory management practices and firm-level moderators, such as staff technical knowledge, to develop a more integrated theoretical account of how inventory-related capabilities jointly shape financial performance in African manufacturing settings.

Suggestions for Further Research

Future studies could extend this work by examining demand forecasting in conjunction with other inventory management practices, incorporating a moderating role for staff working knowledge, and by tracking financial performance longitudinally to assess how the effect of demand forecasting evolves as Cameroonian manufacturing companies adopt more advanced forecasting technologies.

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