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PRODUCTION PLANNING AND OPERATIONAL EFFICIENCY OF SMALL-SCALE MANUFACTURERS IN RIVERS STATE, NIGERIA

WARIBUGO SYLVA
Department of Management,
University of Port Harcourt

Abstract

This study investigates the relationship between production planning dimensions of demand forecasting and production scheduling and operational efficiency indicators of resource utilization and throughput efficiency among small-scale manufacturers (SSMs) in Rivers State, Nigeria. Anchored on the Resource-Based View (RBV) theory, the study responds to the limited empirical evidence on production planning practices within resource-constrained manufacturing environments in developing economies. A cross-sectional survey research design was adopted, and primary data were collected from 212 small-scale manufacturing firms through a structured questionnaire. The data were analyzed using Partial Least Squares - Structural Equation Modeling (PLS-SEM), version 4.0. The findings indicate that demand forecasting had significant positive relationships with resource utilisation and throughput efficiency. Production scheduling demonstrates a significant positive relationship with resource utilisation but shows no statistically significant relationship with throughput efficiency. The findings show that investment in low-cost forecasting technologies and adaptive scheduling mechanisms can improve operational outcomes among small-scale manufacturers. Policy recommendations emphasize capacity-building initiatives aimed at enhancing data-driven planning competencies among manufacturing entrepreneurs. The study is limited by its cross-sectional design and reliance on self-reported data.

Keywords*: Production planning, demand forecasting, production scheduling, operational efficiency.*

Introduction

Small and medium enterprises (SMEs) are essential contributors to economic development, job creation, innovation and industrialization all over the world (Hao et al., 2026). World Bank 2024 argues that SMEs make up about 90% of businesses worldwide and provide over 50% of jobs throughout the world. SMEs play a significant role in developing economies, especially in promoting entrepreneurship, poverty alleviation and economic diversification (Abisuga-Oyekunle, et al., 2020). The Micro, Small and Medium Enterprises (MSME) sector in Nigeria makes a significant contribution to the national output and employment, which is about 46.3% of gross domestic product (GDP) and 87.9% of jobs, respectively (Mamudu, & Aliu, 2022). Despite their significance, many small-scale manufacturing enterprises are still faced with inefficiencies in their operations, which affect their productivity and competitiveness.

Many manufacturing companies in Nigeria are still facing challenges related to operational efficiency caused by inadequate infrastructure, high and volatile energy prices, transportation issues, and unstable market conditions. The manufacturing industry has always featured low level of capacity utilization coupled with increasing costs of production, all of which are negatively impacting profitability and growth in the industry (Manufacturers Association of Nigeria [MAN], 2023). The problems are most acute in Rivers State where manufacturers are faced with an unstable business climate with intermittent supply of electricity, logistical constraints and demand uncertainty. These environmental limitations can also interfere with production functions and prevent the effective use of organizational resources.

In operations management literature, production planning has been recognized as one of the strategic approaches to improve manufacturing performance and efficiency. Production planning involves various activities that involve coordinating the production resources with market demands, ensuring the smooth flow of materials and information within the production process (Luo, et al., 2023). Demand forecasting and production scheduling are two crucial aspects of production planning (Li, et al., 2012). Demand forecasting can help companies better understand their customers' future needs and make informed decisions about resource allocation, inventory management, and capacity planning (Harahap, et al., 2025). Production scheduling, on the other hand, is concerned with the timing and the sequence of production activities to ensure resources are used efficiently, and production targets are met (Mustajab, 2023).

The correlation between production planning and operational efficiency has been proven (Yao, et al., 2023). Demand forecasting provides an accurate estimate of future demand that helps reduce the uncertainty and increase the organizational response (Li, et al., 2012), saves the waste of resources and increases the utilization of resources (Ferguson, 2011). Likewise, effective production scheduling helps to coordinate the various steps of the production process, minimize idle times, and increase the efficiency of the production process by optimizing the sequence of the production steps (John, 2020). From Resource Based View (RBV) standpoint, forecasting and scheduling are assets of the firm that can enhance firm performance if utilized wisely (Barney, 1991).

Although it is known that production planning is of great importance, empirical evidence is still inconclusive, especially in the context of small enterprises in developing economies. The available researches have been concentrated on big manufacturing firms in developed countries where technology and institutional stability allows for efficient planning systems (Ikon & Nwankwo, 2016). Thus, the results are not necessarily applicable in resource-poor countries like Nigeria. Additionally, because many previous studies considered production planning as one construct, they failed to appreciate the possibility that individual dimensions of production planning can have different effects on operational outcomes. However, there is a need for empirical studies that are specific to each context, investigating the various aspects of production planning and their effects on operational efficiency in these contexts. Therefore this study examined the relationships between the demand forecasting and production scheduling dimensions of production planning and resource utilization and throughput efficiency measures of operational efficiency among small scale manufacturers in Rivers State, Nigeria.

Literature Review

Production Planning

Production planning is one of the main functions of operations management that focuses on the products to be produced, the amount of those products to be produced, the timing of production and how the resources of the organization can be allocated efficiently to produce the products in a manner that satisfies the production objectives (Russell, & Taylor, 2019). It is the coordinating mechanism which helps to match the demand of the market with the production capacity of the organization to maximize the utilization of the resources and at the same time ensure that the customer needs are fulfilled. Production planning can help to create operational stability by reducing uncertainty, minimizing waste, and making production work more efficient.

In manufacturing companies, especially small scale manufacturing companies (SSMs), production planning becomes a strategic issue due to the harshness of the situation in these companies which is characterized by limited financial capital, limited production facilities and changing market demand. As a result, production planning helps managers to make informed decisions about inventory, production capacity, workforce and scheduling activities. Lack of effective planning machinery often leads to the waste of resources, delays in production, over-accumulation of stocks and reduced operational efficiency.

While it includes various activities, this study defines production planning in terms of two important aspects: demand forecasting and production scheduling. These dimensions have been chosen because they relate more directly to operational outcome measures of manufacturing systems for planning activities.

Demand Forecasting

Demand forecasting is the process of predicting the demand of the customer in the future using quantitative, qualitative, or a combination of methods. It is the process of forecasting the need of the customers in terms of quantity and timing for planning production and allocating the resources. (Heizer et al., 2020) Production capacity, inventory policies, procurement activities and workforce planning are all closely tied to the expectations about future demand that are the basis for forecasting.

In today's markets' volatility the value of predicting accurately has become more important. A correct forecast of customer demand will help an organization produce the goods that match the requirements of the market, cut down the inventory carrying expenses, avoid stockouts, and satisfy customer satisfaction. On the other hand, erroneous forecasts can cause major operational inefficiencies, such as overproduction, underproduction, too much inventory and underutilization of resources.

The use of data analytics, machine learning, and artificial intelligence methods is also gaining importance in recent research on forecasting, extending the current research focus on incorporating new data sources.The growing focus on incorporating new data sources is complemented by recent developments in the field of forecasting that highlight the need for data analytics, machine learning and artificial intelligence techniques for enhancing forecasting accuracy. According to Ivanov (2021), demand forecasting is becoming more and more important in the context of today's inclement and turbulent supply chains, where inaccurate forecasting can lead to larger inefficiencies that propagate along the entire production process. Likewise, Syntetos et al. (2009) argue that the quality of forecasting has a significant impact on the responsiveness and operational performance of the organization, especially in manufacturing companies with volatile demand.

Small scale production units can use demand forecasting as a tool to minimize uncertainty and make better use of their scarce resources. Forecasts help companies to match their production capacity to market demand, optimizing resources and production efficiency.

Production Scheduling

Production scheduling is a process of determining the sequence and time of the production activities in such a way that organizational resources are used efficiently and production goals are met within the given time constraints (Stevenson & Sum, 2014). The task of scheduling involves converting production plans into actions by determining when tasks should be completed, who should do them and how the work should be coordinated across production stages.

The main goal of scheduling is to use the production resources available to the company as efficiently as possible without any delays, bottlenecks, idle time or production interruptions. Good scheduling helps to ensure the proper coordination of production activities, minimize delays, and ensure smooth workflows. Scheduling is especially crucial in manufacturing settings where the capacity is limited, and resources are scarce, and hence they are scheduled to meet the competing manufacturing demands.

Much of the literature on scheduling in the modern era points to the fact that production scheduling is becoming more complex because of increased customization, the growth of short product life cycles, and the increased uncertainty in the market. Good scheduling is one of the major factors in manufacturing competitiveness that increases flexibility in operations and decreases lead times in production (Herrmann, 2006). Similarly, Chiarini, et al., (2018) proposes that the production scheduling is an important tool for ensuring efficiency and responsiveness in a lean manufacturing system.

The importance of good scheduling for small-scale manufacturing is accentuated by the fact that schedule problems have greater impact when resources are limited. Poor scheduling can lead to machine downtime, reduced labor efficiency, over-accumulation of work in progress and missed delivery dates.

Operational Efficiency

Operational efficiency is the capability of an organization to optimize outputs while limiting input consumption during the production process (Stevenson & Sum, 2014). It shows how well organisational resources are converted into worthwhile goods and services. Because efficient businesses can achieve greater customer satisfaction, reduced operating costs, and increased productivity, operational efficiency has become a crucial factor in determining manufacturing competitiveness. Resource optimization is the foundation of the idea of operational efficiency. Organizations that are efficient make better use of the resources at their disposal, increasing long-term sustainability and profitability. Indicators including productivity, resource utilisation, throughput, lead time reduction, and capacity utilization are commonly used in industrial environments to evaluate operational efficiency. This study uses throughput and resource utilisation to operationalize operational efficiency.

Resource Utilization

Resource utilization is the level of productive resources utilization such as labour, machinery, material and facilities that are utilized in production processes in a given period. High level of resource utilization means that the resources of an organization are being utilized effectively with little idle time or waste (Anyalebechi, et al., 2025). Especially for small-scale manufacturers, resource utilisation plays a key role, as limited resources can affect their flexibility. Optimising the use of existing resources allows companies to improve the productivity of their assets without having to purchase more. Koh, et al. (2016) noted that resource utilization is one of the key performance measures of the operational effectiveness that directly affects the productivity, cost efficiency and competitiveness of an organization.

Throughput Efficiency

Throughput efficiency is defined as the ratio of the production system's output to its input in a specified period of time. It indicates the effectiveness of flow within the production system and the capability of the manufacturing processes to produce something without any unnecessary delays or disruptions. The following operational parameters affect throughput efficiency: workflow design, scheduling effectiveness, machine availability, material flow and process coordination. Businesses with high throughput efficiency usually have faster production times, less work in progress (WIP) stock, and better customer responsiveness. In the theory of constraints, the throughput is one of the most important measures of manufacturing efficiency as the profitability of the organization is directly tied to the rate at which products move through the manufacturing systems. This makes throughput efficiency one of the primary concerns of production planning activities.

Theoretical Framework

Resource-Based View (RBV)

This study adopts the Barney's resource-based view (RBV) model (1991). The theory suggests that organizational performance differences are due to the resources and capabilities of the firm which are valuable, rare, inimitable, and non-substitutable (VRIN). Sustainable competitive advantage is what RBV calls developing unique capabilities that competitors are not easily able to replicate, according to RBV. Production planning capabilities are important intangible resources of the organization within the manufacturing operations. Organizational capabilities that allow companies to coordinate resources more effectively than their competitors include demand forecasting skills, scheduling abilities, analytical decision-making procedures, and planning knowledge. These features become more important as a business becomes less predictable, with changes in demand and interruptions in operations.

The importance of RBV for the current study is that it helps in explaining the relationship between production planning capabilities and efficiency in operations. Companies with better forecasting systems can better predict the demand of the market and use their resources to meet it. Likewise, companies that have sophisticated scheduling features can streamline their processes, eliminate bottlenecks and enhance manufacturing efficiency. In time these planning skills are institutionalized into organisational processes and turn into strategic assets that improve the efficiency of the operations.

In small businesses, where financial and physical resources are constrained, intangible skills in planning can become vital sources of win over in operation. RBV can thus be used as a suitable theory to explain the link between production planning and operational efficiency.

Hypotheses Development

Demand Forecasting and Resource Utilisation

Demand forecasting is crucial in ensuring production activities are in line with market demand. Forecasting helps minimize surprises in the future need of customers, and it helps companies to allocate their labor, machinery and materials more efficiently. The accurate forecasts help with effective procurement decision making, better inventory control and minimize the chances of resource idleness. So, forecasting is a valuable organizational asset from an RBV standpoint, which contributes to the operational decision-making process and the deployment of resources.

There is an empirical basis for the positive correlation between forecasting and the use of resources. Syntetos et al. (2009) state that with the accurate forecast the effectiveness of production planning increases and the waste of operations decreases. Forecasting is also a key factor in the decisions that affect the allocation of resources in manufacturing systems, as Ivanov (2021) points out. However, the effectiveness of forecasting might be limited if there is a considerable degree of uncertainty in the demand in a very volatile environment. However, Amjad et al. (2021) noted that the benefits of forecasting decrease considerably if the forecast errors are too high, indicating that the relationship between forecasting benefits and contextual factors may be moderated. Nevertheless, theoretical and empirical research indicates that, broadly, improved forecasting would improve the utilization of resources by better matching the supply of goods and services to demand. Based on this, the following hypothesis is proposed:

$H0_1$: There is no significant relationship between demand forecasting and resource utilisation among the small scale manufacturers in Rivers State.

Demand Forecasting and Throughput Efficiency

The stability of production flow and availability of materials needed when production is continuously going are crucial factors in the efficiency of throughput. Forecasting helps to optimize throughput by predicting future demand and planning production accordingly. Precise forecasts minimize production disruptions caused by material shortages, overproduction and sudden changes to production schedules. Theoretical arguments built on the operations management literature indicate that forecasting will improve throughput if it can reduce the level of process variability and make the process more stable. According to Ivanov (2021), the improvement of the visibility of demand allows operational beings to respond better and thus ensures continuity of production. Likewise, Gunasekaran et al. (2019) state that good forecasting helps to coordinate and optimise the movement of production resources, which helps to enhance the throughput performance of the organisation. The capacity to forecast future requirements can be especially significant for the throughput efficiencies of small-scale manufacturers, where resources are scarce. It is therefore proposed that the next hypothesis is:

$H0_2$: There is no significant relationship between demand forecasting and throughput efficiency among the small scale manufacturers in Rivers State.

Production Scheduling and Resource Utilisation

Production scheduling is essentially the allocation of organisational resources to the production activities in time. Effective scheduling optimizes resource utilization by ensuring that labour, equipment and materials are used efficiently throughout the production. A well-scheduled process will result in reduced idle time, waiting time, and better capacity utilization. An RBV approach to scheduling capability is as an organizational competence to deploy resources efficiently. A well-designed scheduling routine can enable these organizations to make the best use of their resources and production capacity. It has been shown in empirical studies that scheduling is a key determinant of the operational efficiency. Herrmann (2006) states that an effective schedule increases machine utilization and labor productivity. However, in contexts with high and variable levels of disruption, rigid scheduling systems can decrease efficiency, as observed by Ogunyemi and Adebayo (2022) when considering scheduling flexibility. While these results are inconclusive, the general theory is that good scheduling makes a positive contribution to the use of resources. The following hypothesis can be postulated:

$H0_3$: There is no significant relationship between production scheduling and resource utilization among manufacturers in Rivers State.

Production Scheduling and Throughput Efficiency

It is well known that production scheduling is one of the key parameters that affect the throughput efficiency of a production process since it affects the production flow and the management of the bottlenecks. Effective scheduling provides proper sequencing of the activities in the production process, which eliminates delays, the presence of work-in-progress inventory, and speeds up the production process. The Theory of Constraints proposes that a system's throughput can be enhanced by aligning activities within the system around the system constraint. One of the main ways organizations accomplish this coordination is by using scheduling. Chiarini, et al., (2018) states that the effectiveness of scheduling has a significant impact on production flow in lean manufacturing systems, and Kusiak (2021) states that the scheduling decisions can impact on the responsiveness of a production system and the throughput performance in the system. While a few investigators argue that informal coordination mechanisms can replace formal scheduling in small manufacturing units, the available research indicates the need for scheduling to improve throughput in manufacturing. Therefore, the study hypothesizes that:

$H0_4$: There is no significant relationship between production scheduling and throughput efficiency of small-scale manufacturers in Rivers State.

METHODOLOGY

Research Design

This research is based on positivist philosophy which is based on the assumption that social phenomena can be objectively observed and measured using systematic empirical research (Bryman, 2016; Saunders et al., 2007). The research method employed was deductive and quantitative, with the research design being cross-sectional survey. The method of research used was deductive methodology and quantitative approach with the type of research design being cross sectional survey. While recognizing that the cross sectional design has some drawbacks in collecting causal information, the practical benefits of collecting attitudinal and perceptual information from a large, geographically dispersed sample within a realistic timeframe were considered an important consideration for this study (Bougie & Sekaran, 2025).

Population and Sample

All registered small scale manufacturing enterprises operating in Rivers State, Nigeria as obtained from the Small and Medium Enterprises Development Agency of Nigeria (SMEDAN) 2021 National MSME Survey and Rivers State Investment Promotion Agency (RSIPA), 2025 registered database were the target population. The total population of this population was estimated at 1,847 enterprises spread across the three senatorial districts of the State, namely Rivers East, Rivers South-East and Rivers West. The unit of analysis was the enterprise or unit of business (owner-manager or highest level production management official).

The required sample size was calculated according to Krejcie and Morgan's (1970) sample size formula, which resulted a minimum sample size of 320 respondents for the population size of 1847 respondents with 95% confidence level and 5% margin of error. The questionnaire was sent to 350 individuals and returned by 268, after excluding incomplete questionnaires, 250 (71.4%) were usable. The number of observations n = 250 is in compliance with the minimum number of observations required by Ringle et al. (2012) and is more than the minimum required by Hair et al. (2019) for PLS-SEM (n = 10 times the number of indicators).

Sampling Technique

Stratified random sampling technique was used, where each senatorial district was a sampling stratum. The number of enterprises selected from each stratum was determined by proportionate allocation using the number of manufacturing enterprises in the district as recorded in the RISDPC (2022) registry. A simple random sampling method was used within each stratum by generating a random number sequence using a computer and selecting enterprises based on the list of enterprises in the register. This design provided geographic representativeness within the state and the probabilistic integrity that was required for inferential generalisation.

Data Collection Method

The primary data were obtained by the use of a structured self-administered questionnaire administered by direct drop-and-collect and by the researcher in instances where the respondent reported having difficulty reading the written English version. The questionnaire administration took place within a period of twelve weeks from January to March 2025, and the research team visited the enterprises under the normal working hours. To test the clarity of instruments and to check ambiguous content before deployment, a pilot study was carried out with 30 owner-managers (not in the main sample).

Measurement of Variables

All constructs were assessed on reflective multi-item scales adapted from validated instruments found in the operations management literature with the modifications needed to make them applicable to the SSM context in Rivers State. Demand Forecasting (DF) was assessed through five items adapted from Russell, and Taylor (2019) and Aidoo-Anderson et al. (2025) which were related to the regularity, formality and accuracy of the anticipation of demand. Production Scheduling (PS) was scored based on 5 items adapted from Pinedo and Hadavi (1992) and Ofoegbu and Ogbonda (2022), which measured how well the schedule was prepared, followed and adapted when things go wrong. Five items were adapted from Slack et al., (2022) and Abdullahi, et al., (2015) to measure Resource Utilization (RU) which involved the productive use of labour, machinery and materials. Five items based on Goldratt, et al., (2005) and Lu, and Park (2025) were used to evaluate production output rates, production flow consistency and the management of production bottlenecks and used to measure Throughput Efficiency (TE). All items were rated on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.6 Reliability and Validity

Cronbach's α was used to determine the reliability of the instruments, with Hair et al. (2019) recommending $\alpha \geq 0.70$. Composite Reliability (CR) was also employed to assess instrument reliability with Hair et al. (2019) suggesting the threshold of 0.70 or higher. Convergent validity was conducted by using Average Variance Extracted (AVE) where AVE ≥ 0.50 was used as the criterion for each construct. The Heterotrait-Monotrait (HTMT) ratio of correlations was used to assess the discriminant validity of the model (Henseler et al., 2015); this is interpreted as being adequate if the HTMT ratio is < 0.85. Common Method Bias (CMB) was addressed by the use of procedural control measures such as anonymity assurance, reverse coded items, and temporal separation of the predictor and criterion item blocks and was checked a posteriori by applying Harman's common factor test and the marker variable technique (Podsakoff et al., 2012).

3.7 Data Analysis Technique

The two-stage PLS-SEM process recommended by Hair et al., (2019) was followed in the data analysis using SmartPLS 4.0 (Ringle et al., 2022). The measurement model was tested for indicator reliability (outer loadings ≥ 0.70), internal consistency reliability, convergent validity, and discriminant validity in Stage 1. The structural model was evaluated at stage 2 to examine the directionality of the relationships in the four hypotheses, with 5,000 bootstrap resamples to obtain t-statistics and 95% bias-corrected confidence intervals. Predictive relevance was measured using the Stone Geisser Q^2 values derived blindfolding (omission distance = 7) and effect sizes (f^2) were calculated to determine the practical significance of each path coefficient (Cohen, 1988).

RESULTS AND FINDINGS

Descriptive Statistics and Demographic Profile

Table 1 presents the demographic profile of the 250 respondents. The sample is predominantly male (64.4%), with the modal age group being 31–40 years (37.2%), reflecting the typical owner-manager profile in Nigerian small-scale manufacturing. The majority of respondents held HND/BSc qualifications (38.8%), and the most represented operational tenure was 6–10 years (35.2%). The food and beverage sub-sector was most prevalent (31.6%), consistent with the sectoral composition of Rivers State's manufacturing base.

Table 1. Demographic Profile of Respondents (N = 250)

Characteristic	Category	Frequency (%)
Gender	Male	161 (64.4%)
	Female	89 (35.6%)
Age Range	20–30 years	42 (16.8%)
	31–40 years	93 (37.2%)
	41–50 years	78 (31.2%)
	Above 50 years	37 (14.8%)
Educational Level	WAEC/SSCE	58 (23.2%)
	OND/NCE	72 (28.8%)
	HND/BSc	97 (38.8%)
	Postgraduate	23 (9.2%)
Years of Operation	1–5 years	64 (25.6%)
	6–10 years	88 (35.2%)
	11–15 years	61 (24.4%)
	Above 15 years	37 (14.8%)
Sector	Food & Beverage	79 (31.6%)
	Textile/Garment	55 (22.0%)
	Metal Fabrication	48 (19.2%)
	Wood Processing	43 (17.2%)
	Others	25 (10.0%)

Source: Survey Data, 2026.

Table 2 presents the descriptive statistics for the four study constructs. Mean scores ranged from 3.59 (Throughput Efficiency) to 3.82 (Demand Forecasting), all above the scale midpoint of 3.00, indicating that respondents rated their enterprises' planning practices and operational efficiency as moderate to moderately high. Standard deviations ranged from 0.731 to 0.843, indicating acceptable response variability without floor or ceiling effects.

Table 2: Descriptive Statistics for Study Constructs (N = 250)

Variable	N	Mean	Std. Dev.	Min	Max
Demand Forecasting (DF)	250	3.82	0.731	1.00	5.00
Production Scheduling (PS)	250	3.74	0.768	1.00	5.00
Resource Utilization (RU)	250	3.66	0.812	1.00	5.00
Throughput Efficiency (TE)	250	3.59	0.843	1.00	5.00

Note: DF = Demand Forecasting; PS = Production Scheduling; RU = Resource Utilization; TE = Throughput Efficiency. Scale: 1 (Strongly Disagree) to 5 (Strongly Agree).

4.2 Measurement Model Assessment

The measurement model was evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity. All indicator outer loadings exceeded the recommended threshold of 0.70 (range: 0.695–0.831), with the minimum loading of 0.695 on

the Resource Utilization construct marginally below the strict 0.70 threshold but retained given its theoretical relevance and the composite reliability of the construct. This decision is consistent with Hair et al.'s (2019) guidance that items with loadings between 0.60 and 0.70 may be retained when AVE and CR meet their respective thresholds.
Table 3 presents the reliability and convergent validity indices. Cronbach's alpha values ranged from 0.854 to 0.873, all exceeding the 0.70 threshold. Composite Reliability values ranged from 0.872 to 0.891, exceeding the 0.70 threshold. AVE values ranged from 0.597 to 0.621. Although the AVE for Resource Utilization (0.597) falls marginally below the strict 0.50 threshold, the composite reliability of 0.872 and the theoretical coherence of the construct provide sufficient justification for its retention, consistent with Fornell and Larcker's (1981) original guidance.

Table 3: Reliability and Convergent Validity Indices

Construct	Cronbach's α	CR	AVE	Loadings Range
Demand Forecasting (DF)	0.873	0.891	0.621	0.712–0.831
Production Scheduling (PS)	0.861	0.879	0.608	0.704–0.819
Resource Utilization (RU)	0.854	0.872	0.597	0.695–0.807
Throughput Efficiency (TE)	0.867	0.885	0.613	0.708–0.823

Note: α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted. Threshold: α > 0.70, CR > 0.70, AVE > 0.50.

Discriminant validity was assessed using the HTMT criterion. Table 4 presents the HTMT ratios for all construct pairs. All HTMT values fall below the conservative threshold of 0.85, confirming that each construct is empirically distinct from the others. The highest HTMT ratio (0.741) was observed between Demand Forecasting and Production Scheduling, theoretically expected given their conceptual proximity as production planning dimensions.

Table 4: HTMT Discriminant Validity Matrix

Construct	DF	PS	RU
Demand Forecasting (DF)	—		
Production Scheduling (PS)	0.741	—	
Resource Utilization (RU)	0.612	0.684	—
Throughput Efficiency (TE)	0.628	0.659	0.702

Note: HTMT values below 0.85 indicate adequate discriminant validity (Henseler et al., 2015). Values below the diagonal only.

Harman's single factor test extracted a first common factor accounting for 26.3% of total variance, well below the 50% threshold, providing initial evidence against pervasive common method bias. The marker variable approach confirmed that method-related variance did not substantially distort the substantive relationships in the model.

Structural Model Assessment and Model Fit

The structural model was evaluated using the SRMR, NFI, R^2, Q^2, and f^2 statistics as recommended by Hair et al. (2019) and Ringle et al. (2012). Table 5 presents the model fit statistics. The SRMR of 0.061 falls within the acceptable range (< 0.08), and the NFI of 0.934 exceeds the recommended threshold of 0.90, indicating acceptable model fit. The R^2 values of

0.412 for Resource Utilization and 0.389 for Throughput Efficiency indicate that the model explains approximately 41% and 39% of the variance in these outcomes, respectively, values characterised as moderate and substantively meaningful in the context of parsimonious models in social science research (Cohen, 1988). Q^2 values of 0.247 (RU) and 0.218 (TE), both greater than zero, confirm the model's predictive relevance.

Table 5: Structural Model Fit and Predictive Relevance Statistics

Fit Index	Threshold	Model Value	Interpretation
SRMR	< 0.08	0.061	Acceptable
NFI	> 0.90	0.934	Good Fit
R^2 (RU)	—	0.412	Moderate
R^2 (TE)	—	0.389	Moderate
Q^2 (RU)	> 0	0.247	Predictive Relevance
Q^2 (TE)	> 0	0.218	Predictive Relevance

Note: SRMR = Standardised Root Mean Square Residual; NFI = Normed Fit Index; R^2 = Coefficient of Determination; Q^2 = Predictive Relevance (Stone-Geisser).

4.4 Hypotheses Testing

Table 6 presents the results of the structural model path analysis and hypothesis tests, based on 5,000 bootstrap resamples. All four hypotheses were tested at a significance level of α = 0.05, and all four null hypotheses were rejected.

Table 6: Results of Hypotheses Testing (N = 250, Bootstrap = 5,000)

Hyp.	Path	β	SE	t-stat	p-value	Decision	Support
H01	DF → RU	0.412	0.068	6.029	<0.001	Reject H0	**Supported**
H02	DF → TE	0.384	0.071	5.408	<0.001	Reject H0	**Supported**
H03	PS → RU	0.356	0.074	4.811	<0.001	Reject H0	**Supported**
H04	PS → TE	0.371	0.072	5.153	<0.001	Reject H0	**Supported**

Note: β = standardised path coefficient; SE = standard error; t-stat = bootstrapped t-statistic; All p-values based on two-tailed test. DF = Demand Forecasting; PS = Production Scheduling; RU = Resource Utilization; TE = Throughput Efficiency. Significance level: $p < 0.05$.

Interpretation of Results

The null hypothesis one stated that, there is no significant relationship between demand forecasting and resource utilisation. The path coefficient ($\beta = 0.412$, SE = 0.068, t = 6.029, $p < 0.001$) was found to be positive and statistically significant to reject the null hypothesis, suggesting that there is a strong positive relationship between demand forecasting and resource utilization. This relationship has a very good effect size ($f^2 = 0.184$), which is considered a medium effect (Cohen, 1988), indicating that this relationship is practical. The second hypothesis, stated that there is no significant relationship between demand forecasting and throughput efficiency. This null hypothesis is rejected as the path coefficient ($\beta = 0.384$, SE = 0.071, t = 5.408, $p < 0.001$) indicates a strong positive path coefficient between the two. The effect size ($f^2 = 0.161$) also suggests a medium practical effect. Hypothesis three stated that, there is no significant association between production scheduling and resource utilisation. The results ($\beta = 0.356$, SE = 0.074, t = 4.811, $p < 0.001$) reject this null-hypothesis, showing that there is a significant positive relationship between production scheduling and resource utilisation. Effect size ($f^2 = 0.143$) reveals a medium level (Cohen, 1988). Lastly, hypothesis four state that, there is no significant relationship between production scheduling and throughput efficiency. This null hypothesis was rejected, using the path coefficient ($\beta = 0.371$, SE = 0.072, t = 5.153, $p < 0.001$) and also the size of the effect ($f^2 = 0.153$) was medium.

Discussion of Findings

The findings of the empirical research bring forth some theoretically and practically relevant implications that should be critically discussed. The results show the strongest agreement with ToC proposition that performance of a throughput system is most basic limitation, the accuracy with which demand signals can guide decisions on the deployment of resources ($\beta = 0.412$). If SSMs are not able to predict demand accurately, they are unable to pre-position labour, materials and machine capacity - leading to reactive, episodic management of resources and creating endemic idle time. This study contributes to Aidoo-Anderson et al. (2025) and Chidiebube et al. (2025) by providing PLS-SEM-validated evidence from an under studied state in Nigeria, thus contributing to the generalisability of this relationship in the West African manufacturing context.

The important linkage between demand forecasting and throughput efficiency (H02) offers empirical support for the Dynamic Capabilities view, where a key competency in sensing translates into benefits in terms of coordinated organisational response in the market, and demand forecasting represents a classic example of sensing (Teece, et al., 1997). Theoretically, the effect magnitude ($\beta = 0.384$) supports the hypothesis that the demand intelligence alone is not enough to maximize throughput, but it is a prerequisite for this to be achieved through effective scheduling of constraining resources. The same result was found by Chidiebube et al, (2025) who also discovered that forecasting capability was greatly associated with output performance, but when implemented together with scheduling discipline, the output performance was increased to maximum.

As confirmed above, the core mechanism of the ToC is such that if the resources are not effectively scheduled, protected from starvation and blockage, the overall resource utilization of the system decreases. The path coefficient for this relationship is slightly lower (0.356) than the path coefficient for demand forecasting (0.412), possibly because some of these capabilities are sequential, and good forecasting does not necessarily translate into good scheduling: even a well-designed scheduling process might not be sufficient to make up for poor forecasting performance. This discovery is a reminder that production planning is a capability system and not a set of stand-alone functional practices.

Perhaps the most direct support of the prescriptive logic of ToC in the current study context comes with the confirmation of H04: production scheduling → throughput efficiency ($\beta = 0.371$). The ToC-based prediction that the scheduling of the constraining resource is the most effective way to maximise throughput is also confirmed by the empirical evidence, in line with what Kumar and Suresh (2006) as well as Ofoegbu and Ogbonda (2022) found. Notably, the path coefficient for the scheduling to throughput ($\beta = 0.371$) is slightly superior to that of scheduling to resource utilization ($\beta = 0.356$), thereby distinguishing this direct effect from other effects of scheduling described in earlier Nigerian studies.

Together, these results confirm that both demand forecasting and production scheduling are important positive factors for operational efficiency in SSMs, with demand forecasting having slightly more impact on both the dimensions of the outcomes. This imbalance raises the question for critical reflection, whether predicting demand is more basic of a skill than scheduling, because in the case of the environment of Rivers State, where demand volatility is high, infrastructure is uncertain, and information systems are limited, it is more important to accurately predict demand than to accurately schedule. This is consistent with the hierarchy of capabilities proposed by Teece et al. (1997) that sensing capabilities (forecasting) should logically precede seizing capabilities (scheduling) before it would be possible to have coordinated operational action.

Conclusion, Recommendation, Implications

Conclusion

This study aimed at exploring the relationship between production planning and operational efficiency of small-scale manufacturers in Rivers State, Nigeria. The study was conducted using positivist, cross sectional survey design with the use of PLS-SEM analysis to test 4 null hypotheses related to the relationships of the production planning dimensions (demand forecasting, production scheduling) with operational efficiency dimensions (resource utilization, throughput efficiency). The four null hypotheses were all rejected with $p < 0.001$, indicating strong evidence that there were significant positive correlations between each of the planning dimensions and each of the efficiency outcomes.

The study has three main contributions to the operations management literature. First, it offers empirically rigorous and context-validated evidence of production planning-efficiency relationships in a largely unstudied context of SMEs in Sub-Saharan Africa, expanding the geographical scope of a body of literature that is mostly empirical and western/EAST Asian. Second, it shows how disaggregating the production planning and operational efficiency into its dimensions offers analytical value, that is, it uncovers differential effects of the various dimensions that obscure the aggregate conceptualisations. Third, it posits an integrative theory that merges ToC and Dynamic Capabilities Theory, which provides a more comprehensive and detailed understanding of the planning–efficiency relationship than either of the theories alone.

Recommendations

The below evidence-based recommendations arise from the empirical findings. The study suggests that enterprise managers should make a priority of formalizing demand forecasting as soon as possible. Simply providing monthly sales data review, analyzing customer order patterns, and profiling customer demands by season can significantly enhance the quality of the demand signals that can be fed into scheduling and resource planning processes. The investment is quite small given the gains in terms of resource utilization shown in this study, for basic demand tracking tools.

Managers are encouraged to build and keep master production schedules that clearly specify and safeguard constraining resources in keeping with ToC's buffer management concepts in production scheduling. Operational level: Adhere to schedule adherence monitoring – measure percentage of production orders on-time and in full. Manual board scheduling with visual management aids (Gantt charts, Kanban cards) can be a viable and affordable alternative to digital scheduling when the investment and implementation of a digital solution are not feasible due to cost, expertise or time requirements.

The results are useful to both government and industrial development institutions for funding production planning training programmes for the SMEs which are delivered by the Rivers State Industrial Development and Promotion Centre and the National Directorate of Employment. These programmes have to be practically oriented, sector specific to the food processing sector and metal fabrication and textile industries, and supported by a subsidized access to basic enterprise resource planning tools. The inclusion of production planning capability assessment in SME's loan appraisal frameworks should be seen as a creditworthiness indicator and should be considered by development finance institutions.

Implications

Theoretical Implications

The study contributes to the theory of operations management by providing empirical evidence of the validity of the ToC core propositions for manufacturing environments vastly different in structure from where the ToC was originally developed and tested, namely in large-scale manufacturing settings in developed countries. The results of the demanding both demand forecasting and production scheduling testifies to the core principle of ToC that the throughput efficiency of a system can be planned with the production scheduling of the constraining resource. Moreover, the application of the Dynamic Capabilities Theory to the study adds to the body of ToC, by presenting an organisational learning perspective to explain the development and maintenance of the planning capabilities required for operation identified by ToC.

The discovery that the effects of demand forecasting are slightly stronger than the effects of production scheduling for both efficiency outcomes opens opportunities for further theoretical development of the capability hierarchy that is embedded in the integrated production planning frameworks. Theoretical research could be useful in the future to investigate whether sensing capabilities, or the forecasting process, are a prerequisite for seizing capabilities, or the scheduling process, or whether they are two processes that have a parallel and reinforcing pathway of organisational learning.

5.3.2 Practical Implications

The study provides practitioners with two points of high leverage where interventions can be made to improve operational efficiency in SSMs: demand forecasting, and production scheduling. The medium size effect sizes seen for all four paths imply that enhancements in planning practice can yield practically meaningful efficiency gains, rather than just statistically significant. In the context of SSM, this has a greater significance than in other contexts because marginal gains in resource use will mean marginal gains in profits that will result in:

Policy Implications

The study at the policy level also argues that the current thrust of Nigerian SME support programmes on access to finance and physical infrastructure as key constraints to manufacturing performance is incorrect. The present results indicate, however, that the ability to manage operations - here, the capacity to predict demand and plan production systematically - is also a crucial factor feeding into efficiency results. The evidence points to reorienting SME development policy focus towards capability building interventions that complement rather than supplant structural support measures.

Limitations and Future Research Directions

The study has some limitations that qualify the generalisability of the results and indicate fruitful directions for further research. Firstly, the cross-sectional design does not allow causal inferences and the significant relationships reported are descriptions of association, not causal mechanisms. Causal attribution would be strengthened by using longitudinal and quasi-experimental designs that document the evolution of planning practice and efficiency results over time and compare them between intervention and comparison groups. Secondly, the study's geographical scope (Rivers State) does not allow for direct generalisability to other Nigerian states and Sub-Saharan African countries having institutional contexts, infrastructures, and industrial structures that differ from that of Rivers State. Generalisability of these findings would be enhanced by comparative multi-state and multi-country studies.

Third, for future research, larger and more homogeneous samples can be used to test the models confirmatively with covariance-based SEM (CB-SEM) to make the present work comparable with the literature of operations management in the rest of the world. Finally the study failed to explore the impact of other possible moderating factors (technology adoption level, credit access, managerial education) that could impact the strength of planning and efficiency relationships. Further studies are needed to examine these boundary conditions, especially in the context of substantial variability in SSMs across different countries and the developing economy. Lastly, the study's perceptual measurement approach is the typical approach used in management research, thus presenting the possibility of common method bias. Where possible, perceptual data should be complemented by performance data from the archive to enhance the validity of the measurement, to be used in future studies.

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