



## Automated Production Scheduling Systems and Cost Reduction Among Pharmaceutical Manufacturing Firms in South-East Nigeria

Udeh, Ifeyinwa Ebere, Ph.D.<sup>1</sup>, Chisom, Kelvin Ikeri<sup>2</sup> & Chima, Chima Chukwu<sup>3</sup>

### Abstract

This study examined the effect of automated production scheduling systems on cost reduction among pharmaceutical manufacturing firms in South-East Nigeria. The specific objectives were to examine the effect of automated production planning on labour cost and determine the effect of automated production scheduling on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria. The study was conducted in South-East Nigeria and adopted a descriptive survey research design. The population comprised 798 employees of selected pharmaceutical manufacturing firms across the states in South-East Nigeria. A sample size of 259 respondents was determined using Freund and Williams' statistical formula. Data were collected using a structured questionnaire. Of the 259 questionnaires administered, 252 were duly completed and returned, representing a response rate of approximately 97.3%. The validity of the research instrument was assessed using content validity, while its reliability was tested using the Pearson correlation coefficient, which yielded a reliability coefficient of 0.870, indicating good reliability. Data were presented and analysed using mean scores and standard deviations, while the hypotheses were tested using the Z-test statistic. The findings revealed that automated production planning had a statistically significant positive effect on labour cost,  $Z = 10.079$ ,  $p < .05$ . The findings also indicated that automated production scheduling had a statistically significant positive effect on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria,  $Z = 10.457$ ,  $p < .05$ . The study concluded that automated production scheduling systems could contribute significantly to cost reduction among pharmaceutical manufacturing firms in South-East Nigeria. The study recommended, among other measures, that management of pharmaceutical manufacturing firms in South-East Nigeria should adopt automated production planning systems that align employee schedules with production requirements and available resources

**Keywords:** Automated production planning, automated production scheduling, cost reduction, operational cost reduction, pharmaceutical manufacturing firms.

**Cite:** Udeh, I. E., Chisom, K. I. & Chima, C. C. (2026). Automated Production Scheduling Systems and Cost Reduction Among Pharmaceutical Manufacturing Firms in South-East Nigeria. *International Journal of Management Foresight and Strategy*, 4(7), 567- 585. <https://doi.org/10.5281/zenodo.23419113>

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| Authors | Affiliation                                                                                                                |
|---------|----------------------------------------------------------------------------------------------------------------------------|
| 1       | Department of Business Administration, Enugu state University of Science and Technology. Enugu State.                      |
| 2       | Department of Commercial, Business and industrial Law, Faculty of Law, Imo State University, Imo State.                    |
| 3.      | ESUT Business School, Department of Business Administration, Enugu state University of Science and Technology. Enugu State |

## **Introduction**

Production scheduling in pharmaceutical manufacturing has evolved from traditional manual planning, paper-based production timetables, and supervisor-directed work allocation to computerized and automated scheduling systems. In the past, pharmaceutical manufacturers relied on production managers to arrange manufacturing activities, assign equipment and employees, coordinate raw materials, and determine when each production batch should be processed. Although these methods supported production, they could result in scheduling conflicts, idle equipment, delayed production, and unnecessary operating expenses. The development of computer-based planning, optimization algorithms, and intelligent manufacturing technologies has enabled firms to automate production schedules, improve resource allocation, and coordinate manufacturing activities more efficiently. Li (2026) demonstrated the relevance of optimized scheduling to pharmaceutical manufacturing, showing that improved scheduling can reduce production time and costs while increasing equipment utilization.

Automated production scheduling systems refer to digital technologies and software applications used to plan, organize, sequence, and monitor production activities automatically according to available resources, production targets, equipment capacity, and delivery deadlines. In pharmaceutical manufacturing, these systems help coordinate production batches, equipment usage, material availability, cleaning procedures, and quality inspections. They can improve the use of labour and equipment, minimize production interruptions, reduce unnecessary waiting time, and support timely completion of manufacturing activities. Li (2026) found that an optimized scheduling approach in a pharmaceutical manufacturing setting reduced total production costs by 6.3%, illustrating the potential financial benefits of effective scheduling.

Globally, pharmaceutical manufacturing firms face increasing pressure to control production expenses while maintaining product quality, safety, and regulatory compliance. Automated production scheduling systems help manufacturers coordinate production activities, improve equipment utilization, minimize material wastage, and reduce costs associated with delays and inefficient resource allocation. Li (2026) reported that optimized pharmaceutical production scheduling reduced total production costs and inventory expenses in the manufacturing setting examined. These findings demonstrate the potential contribution of automated scheduling to cost efficiency, although the results may vary across firms depending on their technology, production processes, and resources.

Cost reduction refers to the deliberate and continuous effort by an organization to lower the expenses incurred in producing goods or providing services without compromising quality, safety, or operational effectiveness. It involves controlling labour expenses, minimizing material wastage, reducing equipment downtime, managing energy consumption, and eliminating unnecessary operational activities. Muoneke and Dandago (2024) examined activity-based costing in the Nigerian pharmaceutical industry and highlighted its usefulness in identifying cost-effective production methods and improving production management. Their study reinforces the importance of systematic cost management in pharmaceutical manufacturing.

In Nigeria, pharmaceutical manufacturing firms face the need to manage production expenses efficiently while maintaining the quality and availability of medicines. Adeshina and Abu-Saeed (2024) examined awareness and adoption of emerging technologies among pharmaceutical manufacturing industries in Nigeria following the COVID-19 pandemic, highlighting the relevance of technological development to the industry. Automated production scheduling systems may help Nigerian manufacturers coordinate production resources, reduce avoidable delays, and improve cost control. However, the benefits may be limited by inadequate technological infrastructure, implementation costs, and shortages of relevant technical skills.

In South-East Nigeria, pharmaceutical manufacturing firms need effective production planning to manage labour, equipment, raw materials, energy, and other operating expenses. Inefficient scheduling may contribute to equipment idleness, production delays, material wastage, and increased operating costs. Automated production scheduling systems could help address these challenges by improving production coordination and resource utilization. However, the extent to which automated production planning and automated production scheduling contribute to labour cost management and operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria requires further investigation. Therefore, this study examines the effect of automated production scheduling systems on cost reduction among pharmaceutical manufacturing firms in South-East Nigeria.

### **Statement of the Problem**

The ideal situation is that pharmaceutical manufacturing firms in South-East Nigeria should adopt effective automated production scheduling systems to coordinate production activities, optimize resource utilization, minimize wastage, and reduce operating costs. These systems are expected to improve production planning, ensure efficient allocation of labour and equipment, and enable manufacturing activities to be completed within the required time and budget.

However, some pharmaceutical manufacturing firms may experience challenges such as inadequate technological infrastructure, high implementation costs, limited technical skills, and continued dependence on manual production scheduling methods. These challenges may result in inefficient labour utilization, equipment downtime, production delays, material wastage, and increased operational expenses.

If these problems persist, the firms may experience rising production costs, reduced profitability, poor resource utilization, and declining competitiveness in the pharmaceutical market. Therefore, this study seeks to examine the effect of automated production scheduling systems on cost reduction among pharmaceutical manufacturing firms in South-East Nigeria, with particular attention to automated production planning and labour cost, as well as automated production scheduling and operational cost reduction.

### **Objectives of the Study**

The main objective of the study was to examine the effect of automated production scheduling systems on cost reduction among pharmaceutical manufacturing firms in South-East Nigeria. The specific objectives are to:

- i. Examine the effect of automated production planning on labour cost among pharmaceutical manufacturing firms in South-East Nigeria.
- ii. Determine the effect of automated production scheduling on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria.

#### **Research Questions**

- i. What is the effect of automated production planning on labour cost among pharmaceutical manufacturing firms in South-East Nigeria?
- ii. What is the effect of automated production scheduling on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria?

#### **Statement of Research Hypotheses**

- i. Automated production planning has no significant effect on labour cost among pharmaceutical manufacturing firms in South-East Nigeria.
- ii. Automated production scheduling has no significant effect on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria.

#### **Significance of the Study**

This study will help management of pharmaceutical manufacturing firms in South-East Nigeria identify which dimensions of automated production scheduling systems genuinely support cost reduction, and will contribute to academic literature on the subject in this specific context.

#### **Scope of the Study**

The study covers pharmaceutical manufacturing firms in South-East Nigeria, examining automated production planning and automated production scheduling in relation to labour cost and operational cost reduction respectively.

#### **Review of Related Literature**

##### **Conceptual Review**

##### **Automated Production Scheduling Systems**

Nwamekwe, Mgbemena, Igbokwe and Okpala (2024) describe automated production scheduling systems as computerised systems that use sensor data, forecasting models and scheduling algorithms to plan, monitor and adjust manufacturing activities with minimal manual intervention, replacing paper-based and manually coordinated production arrangements. Such systems typically integrate production forecasting, material planning and scheduling functions into a single platform that provides real-time feedback to production managers (Nwamekwe et al., 2024). In pharmaceutical manufacturing, where production must satisfy strict regulatory and batch-tracing requirements, automated production scheduling systems help firms coordinate complex, multi-stage production activities while keeping costs under control.

### **Components of Automated Production Scheduling Systems**

The following are components of automated production scheduling systems according to the following authors: Automated Production Planning, Automated Production Scheduling, Automated Inventory Scheduling, Automated Workforce Scheduling, and Automated

Maintenance Scheduling (Nwamekwe, Mgbemena, Igbokwe & Okpala, 2024; Yao, Almatooq, Askin & Gruber, 2022; Ouahabi, Chebak, Kamach, Laayati&Zegrari, 2024; Gallo, Mazzuto, Ciarapica& Bevilacqua, 2023).

### **Components of Automated Production Scheduling Systems that formed part of the objectives**

Of the components identified above, this study focuses on two that are most directly implicated in cost reduction: automated production planning and automated production scheduling. These two were selected because they correspond respectively to the two specific objectives of the study and capture, respectively, the forward-planning and the day-to-day sequencing dimensions of automated production coordination.

#### **Automated Production Planning**

Nwamekwe, Mgbemena, Igbokwe and Okpala (2024) describe automated production planning as the use of computerised forecasting and material-planning tools to determine, in advance, the quantities, timing and resources required for future production runs, based on demand forecasts, current production capacity and raw material availability. In manufacturing firms, automated production planning typically draws on historical production data and forecasting models to project workforce and material requirements ahead of production, reducing the need for last-minute manual adjustments to staffing and input allocation.

#### **Automated Production Scheduling**

Ouahabi, Chebak, Kamach, Laayati and Zegrari (2024) describe automated production scheduling as the use of computerised systems, including digital twin and optimisation-based tools, to determine the sequence, timing and allocation of specific production tasks to available machines and personnel, adjusting dynamically as production conditions change. Unlike production planning, which sets out broader production targets in advance, automated production scheduling governs the detailed, day-to-day sequencing of operations on the shop floor (Ouahabi et al., 2024).

#### **Cost Reduction**

Muoneke and Dandago (2024) describe cost reduction as the deliberate and systematic effort by a firm to lower the amount of resources expended in producing goods or delivering services, without compromising product quality, through improved production methods, better resource allocation and the elimination of waste. Cost reduction differs from simple cost control in that it seeks a genuine, lasting decrease in the level of costs incurred rather than merely keeping costs within a set budget (Muoneke&Dandago, 2024). In pharmaceutical manufacturing firms, where raw material, regulatory compliance and energy expenses are substantial, cost reduction is central to sustaining profitability amid competitive and regulatory pressure.

### **Components of Cost Reduction**

The following are components of cost reduction according to the following authors: Labour Cost, Operational Cost, Material Cost, Overhead Cost, and Energy Cost (Muoneke&Dandago, 2024; Oyedare&Oyedokun, 2025; Li, 2026; Yao, Almatooq, Askin & Gruber, 2022).

### **Components of Cost Reduction that formed part of the objectives**

This study adopts two components of cost reduction that correspond to its two specific objectives: labour cost and operational cost reduction. These two components were selected because the first captures the personnel-related expenditure directly affected by automated production planning, while the second captures the broader running expenditure of the production process directly affected by automated production scheduling.

#### **Labour Cost**

Oyedare and Oyedokun (2025) describe labour cost as the total expenditure a firm incurs on its workforce in the course of production, including wages, overtime payments, training costs and other personnel-related expenses tied to the staffing of production activities. Labour cost is one of the cost drivers most sensitive to how efficiently a firm plans its workforce requirements against actual production needs, since poor planning tends to produce either idle labour or costly overtime (Oyedare&Oyedokun, 2025).

#### **Operational Cost Reduction**

Li (2026) describes operational cost reduction as the lowering of the day-to-day running expenditure of a production process, including energy, inventory holding, equipment changeover and other costs directly tied to how production activities are sequenced and executed on the shop floor. Operational cost reduction is closely tied to scheduling efficiency, since better sequencing of production tasks reduces idle equipment time, inventory build-up and other avoidable expenditure without requiring additional capital investment (Li, 2026).

### **Pharmaceutical Manufacturing Firms in South-East Nigeria**

Obodoagu, Ogbuke and Nwokeukwu (2024) describe pharmaceutical manufacturing firms in South-East Nigeria as registered drug manufacturing companies operating within the South-East geopolitical zone, engaged in the production of essential and specialised pharmaceutical products under the regulatory oversight of the National Agency for Food and Drug Administration and Control (NAFDAC). These firms typically face significant raw material, energy and labour cost pressures, and increasingly look to production automation as a means of controlling costs while meeting stringent regulatory and quality requirements (Obodoagu et al., 2024).

## Conceptual Framework

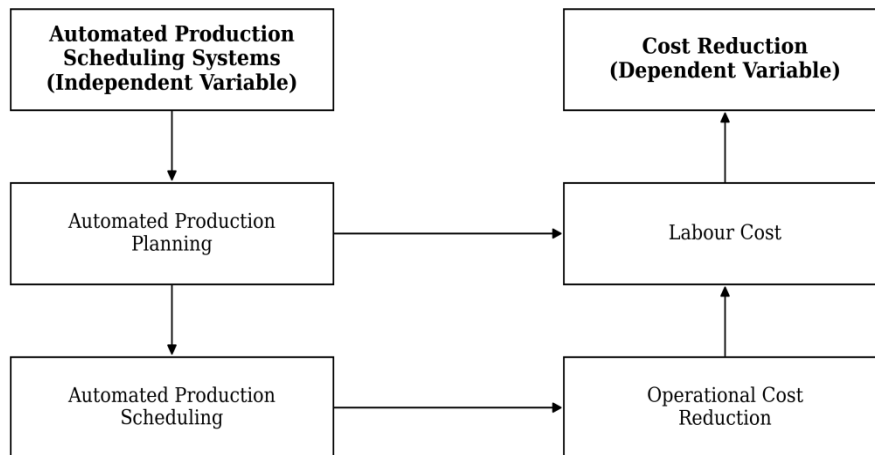


**Fig. 1: Conceptual Framework on Automated Production Scheduling Systems and Cost Reduction**

*Source: Researcher's Conceptualization, 2026*

The diagram shows that automated production planning is linked to labour cost, while automated production scheduling is associated with operational cost reduction. Together, these dimensions of automated production scheduling systems are depicted as drivers of cost reduction among pharmaceutical manufacturing firms in South-East Nigeria.

## Theoretical Framework

The following theories guided the study:

- i. **Scientific Management Theory by Taylor (1911)**
- ii. **Theory of Constraints by Goldratt (1984)**

### Scientific Management Theory by Taylor (1911)

Scientific Management Theory, advanced by Frederick Winslow Taylor in 1911, holds that production efficiency and cost control are best achieved by systematically studying work methods, standardising procedures, and planning labour deployment in advance rather than leaving work arrangements to informal custom or individual worker discretion. Taylor argued that deliberate, data-informed planning of tasks and labour allocation removes wasted time and effort, thereby lowering the labour cost of production.

Applied to this study, Scientific Management Theory explains why automated production planning, by systematically forecasting workforce and material requirements ahead of production, reduces idle labour time and costly overtime, thereby lowering labour cost. This theory anchors the study's first objective, on automated production planning and labour cost.

### **Theory of Constraints by Goldratt (1984)**

The Theory of Constraints, developed by Eliyahu Goldratt in 1984, holds that the overall performance and cost efficiency of a production system is determined by its most limiting constraint or bottleneck, and that systematically identifying and managing this constraint, including through improved sequencing and scheduling of production tasks, is the most effective route to reducing operating costs and improving throughput. The theory emphasises continuous scheduling adjustment around the constraint rather than uniform improvement across all stages of production.

Applied to this study, the Theory of Constraints explains why automated production scheduling, by continuously sequencing and reallocating production tasks around bottlenecks and equipment availability, reduces idle equipment time, inventory build-up and other avoidable running expenditure, thereby supporting operational cost reduction. This theory anchors the study's second objective, on automated production scheduling and operational cost reduction.

### **Empirical Review**

#### **Automated Production Planning and Labour Cost**

Sharma, Patel and Shah (2023), in a comprehensive review of Industry 4.0 adoption in the pharmaceutical industry for sustainable development, found that core Industry 4.0 technologies, including artificial intelligence and automated planning systems, enabled pharmaceutical manufacturers to better match workforce deployment to forecasted production needs, reducing instances of overstaffing and idle labour time across the production cycle. This study is relevant as it demonstrates, specifically within the pharmaceutical sector, that automated planning technologies help firms align labour deployment with actual production requirements, directly bearing on labour cost.

Gallo, Mazzuto, Ciarapica and Bevilacqua (2023), in a systematic literature review of artificial intelligence applications to production scheduling problems in real industrial settings, found that AI-driven planning and scheduling tools consistently reduced the manual planning workload placed on production personnel across the studies reviewed, while also improving planning accuracy compared with manually developed production plans. This study is relevant as it demonstrates, across a wide range of industrial settings, that automated planning tools reduce the labour burden associated with production planning, a mechanism directly relevant to the present study's first objective.

Nwamekwe, Mgbemena, Igbokwe and Okpala (2024) designed and implemented an Automated Production Planning and Control Device (APPCD) for a textile manufacturing firm in Nigeria, using a hybrid SARIMA-LSTM forecasting model to plan material requirements and product-mix scheduling from five years of production data. Their findings showed that the automated planning device reduced delivery delays and processing time compared with the firm's previous manual planning approach, and improved productivity to 1.32 metres-per-unit with a system efficiency of 79.8 percent, outcomes that reduce the need for costly manual overtime and rework. This study is relevant as it provides direct evidence, from a Nigerian manufacturing context, that automated production planning improves workforce and resource allocation in ways that constrain labour cost.

Knoll, Steinberger, Kuchler, Azimi, Tranninger, Sacher and Horn (2025) designed and experimentally evaluated a scheduling optimisation approach for a compact end-to-end pharmaceutical manufacturing line, incorporating automated planning of production stages to minimise idle time between processing steps. Their findings showed that the automated planning approach reduced the manual coordination effort previously required to keep production stages synchronised, lowering the labour hours needed to supervise and adjust the line manually. This study is relevant as it shows, in a pharmaceutical manufacturing context, that automated planning of production stages reduces the labour input required for production coordination.

Li (2026), in a study of scheduling efficiency and production costs in a pharmaceutical intelligent manufacturing workshop using an improved particle swarm optimisation algorithm, found that improved scheduling efficiency, achieved partly through automated production planning of batch sequencing, reduced labour costs by 8.1 percent over a six-month period, an outcome attributed to reduced overtime and better-optimised personnel allocation. This study is relevant as it provides direct, pharmaceutical-specific empirical evidence that automated planning of production activities lowers labour cost.

#### **Automated Production Scheduling and Operational Cost Reduction**

Miguel, Coito, Firme, Costigliola, Figueiredo, Vieira and Sousa (2023) developed a scheduling approach for minimising total completion time in large-sized pharmaceutical quality control scheduling problems, tested against real quality-control laboratory data. Their findings showed that the automated scheduling approach substantially reduced total completion time for quality-control batches compared with existing manual scheduling practice, thereby reducing the operational costs associated with delayed batch release and laboratory idle time. This study is relevant as it demonstrates that automated scheduling in a pharmaceutical-specific process reduces the operational costs tied to production and quality-control delays.

Ouahabi, Chebak, Kamach, Laayati and Zegrari (2024), in a review of digital twin applications to dynamic production scheduling, found that digital twin-enabled scheduling systems allowed manufacturers to continuously adjust production sequences in response to real-time shop-floor conditions, consistently reducing equipment downtime and the operational costs associated with unplanned production interruptions across the studies reviewed. This study is relevant as it shows that dynamic, technology-enabled scheduling reduces the operational costs tied to equipment downtime and production disruption.

Liu, Gui, Li and Liu (2025) proposed a slack-based, two-stage improved particle swarm optimisation algorithm for robust scheduling of a flexible job-shop handling both new and remanufacturing jobs under production uncertainty. Their findings showed that the automated scheduling algorithm maintained low operational cost outcomes even under disrupted production conditions, outperforming conventional scheduling approaches in minimising the cost impact of schedule disruptions. This study is relevant as it demonstrates that automated scheduling systems can sustain operational cost reduction even where production conditions are uncertain or subject to disruption.

Reshma, Sarkar, Varun and Jignesh (2025) examined the integration of artificial intelligence and Internet of Things sensor data in pharmaceutical manufacturing, analysing how machine-learning-driven monitoring and scheduling adjustments affected production continuity. Their findings showed that analysing sensor data through machine

learning algorithms to inform scheduling decisions effectively reduced unplanned downtime and improved production efficiency, lowering the operational costs associated with unscheduled equipment stoppages. This study is relevant as it provides pharmaceutical-specific evidence that automated, sensor-informed scheduling adjustments reduce the operational costs of unplanned downtime.

Li (2026), in the same study of a pharmaceutical intelligent manufacturing workshop, found that an improved particle swarm optimisation scheduling algorithm increased equipment utilisation from 68.5 percent to 82.3 percent, shortened average flow time by 28.4 hours, and reduced total production costs by 6.3 percent, with energy costs and inventory costs falling by 14.9 percent and 36.8 percent respectively, and indirect costs overall falling by 42.3 percent. This study is relevant as it provides direct, pharmaceutical-specific evidence that automated production scheduling substantially reduces operational costs, particularly indirect costs tied to inventory and energy use.

### Methodology

The area of study was South East, Nigeria. The study adopted a descriptive survey research design. The population comprised 798 employees of selected pharmaceutical manufacturing firms across Abia, Anambra, Ebonyi, Enugu, and Imo States. A sample size 259 was determined using Freund and William's statistic formula, Data were collected through a structured questionnaire. Two hundred and fifty two (252) staff returned the questionnaire and accurately filled. That gave 97 percent response rate. The validity of the instrument was tested using content analysis and the result was good. The reliability was tested using the Pearson correlation coefficient (r). It gave a reliability co-efficient of 0.870 which was also good. Data was presented and analyzed by mean score (3.0 and above agreed while below 3.0 disagreed) and standard deviation using Sprint Likert Scale. The hypotheses were analyzed using Z - test statistic tool.

### Data Presentation and Analysis

#### The effect of automated production planning on labour cost among pharmaceutical manufacturing firms in South-East Nigeria

**Table 1: Responses on the effect of automated production planning on labour cost among pharmaceutical manufacturing firms in South-East Nigeria**

| S/N | Statement                                                                                                          | 5<br>SA | 4<br>A | 3<br>N | 2<br>DA | 1<br>SD | ΣFX   | $\bar{X}$ | SD    | Decision |
|-----|--------------------------------------------------------------------------------------------------------------------|---------|--------|--------|---------|---------|-------|-----------|-------|----------|
| 1   | Automated production planning helps our firm reduce the number of labour hours required for production activities. | 685     | 344    | 18     | 18      | 14      | 1079  |           |       |          |
|     |                                                                                                                    | 137     | 86     | 6      | 9       | 14      | 252   | 4.28      | 1.066 | Agree    |
|     |                                                                                                                    | 54.4    | 34.1   | 2.4    | 3.6     | 5.6     | 100.0 |           |       |          |
| 2   | Automated production planning minimizes labour costs by improving the                                              | 665     | 336    | 18     | 48      | 5       | 1072  |           |       |          |
|     |                                                                                                                    | 133     | 84     | 6      | 24      | 5       | 252   | 4.25      | 1.025 | Agree    |

| S/N                                     | Statement                                                                                                | 5    | 4    | 3   | 2   | 1   | ΣFX   | $\bar{X}$ | SD    | Decision |
|-----------------------------------------|----------------------------------------------------------------------------------------------------------|------|------|-----|-----|-----|-------|-----------|-------|----------|
|                                         |                                                                                                          | SA   | A    | N   | DA  | SD  |       |           |       |          |
|                                         | allocation of employees to production tasks.                                                             | 52.8 | 33.3 | 2.4 | 9.5 | 2.0 | 100.0 |           |       |          |
| 3                                       | The use of automated production planning reduces overtime expenses in our firm.                          | 720  | 276  | 18  | 32  | 17  | 1063  |           |       |          |
|                                         |                                                                                                          | 144  | 69   | 6   | 16  | 17  | 252   | 4.22      | 1.189 | Agree    |
|                                         |                                                                                                          | 57.1 | 27.4 | 2.4 | 6.3 | 6.7 | 100.0 |           |       |          |
| 4                                       | Automated production planning improves employee productivity and reduces unnecessary labour expenditure. | 720  | 308  | 18  | 40  | 5   | 1091  |           |       |          |
|                                         |                                                                                                          | 144  | 77   | 6   | 20  | 5   | 252   | 4.33      | 0.993 | Agree    |
|                                         |                                                                                                          | 57.1 | 30.6 | 2.4 | 7.9 | 2.0 | 100.0 |           |       |          |
| 5                                       | Automated production planning helps our firm control overall labour costs.                               | 720  | 308  | 18  | 40  | 5   | 1091  |           |       |          |
|                                         |                                                                                                          | 144  | 77   | 6   | 20  | 5   | 252   | 4.33      | 0.993 | Agree    |
|                                         |                                                                                                          | 57.1 | 30.6 | 2.4 | 7.9 | 2.0 | 100.0 |           |       |          |
| Total Grand mean and standard deviation |                                                                                                          |      |      |     |     |     |       | 4.28      | 1.053 |          |

**Source: Field Survey, 2026**

Table 1 shows that 223 respondents out of 252 representing 88.5 percent agreed that Automated production planning helps our firm reduce the number of labour hours required for production activities, with a mean score of 4.28 and standard deviation of 1.066. 217 respondents out of 252 representing 86.1 percent agreed that Automated production planning minimizes labour costs by improving the allocation of employees to production tasks, with a mean score of 4.25 and standard deviation of 1.025. 213 respondents out of 252 representing 84.5 percent agreed that The use of automated production planning reduces overtime expenses in our firm, with a mean score of 4.22 and standard deviation of 1.189. 221 respondents out of 252 representing 87.7 percent agreed that Automated production planning improves employee productivity and reduces unnecessary labour expenditure, with a mean score of 4.33 and standard deviation of 0.993. 221 respondents out of 252 representing 87.7 percent agreed that Automated production planning helps our firm control overall labour costs, with a mean score of 4.33 and standard deviation of 0.993.

**The effect of automated production scheduling on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria**

**Table 2: Responses on the effect of automated production scheduling on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria**

| S/N                                     | Statement                                                                                                        | 5    | 4    | 3   | 2   | 1   | ΣFX   | X̄   | SD    | Decision |
|-----------------------------------------|------------------------------------------------------------------------------------------------------------------|------|------|-----|-----|-----|-------|------|-------|----------|
|                                         |                                                                                                                  | SA   | A    | N   | DA  | SD  |       |      |       |          |
| 1                                       | Automated production scheduling helps our firm reduce operational costs by minimizing production delays.         | 720  | 316  | 18  | 24  | 11  | 1089  |      |       |          |
|                                         |                                                                                                                  | 144  | 79   | 6   | 12  | 11  | 252   | 4.32 | 1.039 | Agree    |
|                                         |                                                                                                                  | 57.1 | 31.3 | 2.4 | 4.8 | 4.4 | 100.0 |      |       |          |
| 2                                       | Automated production scheduling improves the utilization of production equipment and reduces operating expenses. | 720  | 304  | 18  | 24  | 14  | 1080  |      |       |          |
|                                         |                                                                                                                  | 144  | 76   | 6   | 12  | 14  | 252   | 4.29 | 1.099 | Agree    |
|                                         |                                                                                                                  | 57.1 | 30.2 | 2.4 | 4.8 | 5.6 | 100.0 |      |       |          |
| 3                                       | The use of automated production scheduling reduces material wastage and unnecessary production costs.            | 720  | 304  | 18  | 24  | 14  | 1080  |      |       |          |
|                                         |                                                                                                                  | 144  | 76   | 6   | 12  | 14  | 252   | 4.29 | 1.099 | Agree    |
|                                         |                                                                                                                  | 57.1 | 30.2 | 2.4 | 4.8 | 5.6 | 100.0 |      |       |          |
| 4                                       | Automated production scheduling minimizes machine downtime and associated maintenance expenses.                  | 720  | 304  | 18  | 24  | 14  | 1080  |      |       |          |
|                                         |                                                                                                                  | 144  | 76   | 6   | 12  | 14  | 252   | 4.29 | 1.099 | Agree    |
|                                         |                                                                                                                  | 57.1 | 30.2 | 2.4 | 4.8 | 5.6 | 100.0 |      |       |          |
| 5                                       | Automated production scheduling contributes to a reduction in the overall operational costs of our firm.         | 720  | 340  | 18  | 0   | 17  | 1095  |      |       |          |
|                                         |                                                                                                                  | 144  | 85   | 6   | 0   | 17  | 252   | 4.35 | 1.043 | Agree    |
|                                         |                                                                                                                  | 57.1 | 33.7 | 2.4 | 0.0 | 6.7 | 100.0 |      |       |          |
| Total Grand mean and standard deviation |                                                                                                                  |      |      |     |     |     |       | 4.31 | 1.076 |          |

**Source: Field Survey, 2026**

Table 2 shows that 223 respondents out of 252 representing 88.5 percent agreed that Automated production scheduling helps our firm reduce operational costs by minimizing production delays, with a mean score of 4.32 and standard deviation of 1.039. 220 respondents out of 252 representing 87.3 percent agreed that Automated production scheduling improves the utilization of production equipment and reduces operating expenses, with a mean score of 4.29 and standard deviation of 1.099. 220 respondents out of 252 representing 87.3 percent agreed that The use of automated production scheduling reduces material wastage and unnecessary production costs, with a mean score of 4.29 and standard deviation of 1.099. 220 respondents out of 252 representing 87.3 percent agreed that Automated production scheduling minimizes machine downtime and associated maintenance expenses, with a mean score of 4.29 and standard deviation of 1.099. 229 respondents out of 252 representing 90.9 percent agreed

that Automated production scheduling contributes to a reduction in the overall operational costs of our firm, with a mean score of 4.35 and standard deviation of 1.043.

### Test of Hypotheses

**Test of Hypotheses One: Automated production planning has no significant effect on labour cost among pharmaceutical manufacturing firms in South-East Nigeria.**

#### One-Sample Kolmogorov-Smirnov Test

|                                   |          | Automated production planning helps our firm reduce the number of labour hours required for production activities. | Automated production planning minimizes labour costs by improving the allocation of employees to production tasks. | The use of automated production planning reduces overtime expenses in our firm. | Automated production planning improves employee productivity and reduces unnecessary labour expenditure. | Automated production planning helps our firm control overall labour costs. |
|-----------------------------------|----------|--------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| N                                 |          | 252                                                                                                                | 252                                                                                                                | 252                                                                             | 252                                                                                                      | 252                                                                        |
| Uniform Parameters <sup>a,b</sup> | Minimum  | 1                                                                                                                  | 1                                                                                                                  | 1                                                                               | 1                                                                                                        | 1                                                                          |
|                                   | Maximum  | 5                                                                                                                  | 5                                                                                                                  | 5                                                                               | 5                                                                                                        | 5                                                                          |
| Most Extreme Differences          | Absolute | .635                                                                                                               | .611                                                                                                               | .595                                                                            | .627                                                                                                     | .627                                                                       |
|                                   | Positive | .056                                                                                                               | .020                                                                                                               | .067                                                                            | .020                                                                                                     | .020                                                                       |
|                                   | Negative | -.635                                                                                                              | -.611                                                                                                              | -.595                                                                           | -.627                                                                                                    | -.627                                                                      |
| Kolmogorov-Smirnov Z              |          | 10.079                                                                                                             | 9.701                                                                                                              | 9.449                                                                           | 9.953                                                                                                    | 9.953                                                                      |
| Asymp. Sig. (2-tailed)            |          | .000                                                                                                               | .000                                                                                                               | .000                                                                            | .000                                                                                                     | .000                                                                       |

a. Test distribution is Uniform.

b. Calculated from data.

### Decision Rule:

Since the calculated z-value (10.079) > critical z-value (.000) at the 5% significance level, we reject the null hypothesis

### Decision:

Furthermore, comparing the calculated Z- value ranges from 9.449 < 10.079 against the critical Z- value of .000 (2-tailed test at 95percent level of confidence) the null hypothesis were rejected. Thus the alternative hypothesis was accepted which states that Automated production planning had significant positive effect on labour cost among pharmaceutical manufacturing firms in South-East Nigeria.

**Test of Hypotheses Two: Automated production scheduling has no significant effect on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria.**

**One-Sample Kolmogorov-Smirnov Test**

|                                   |          | Automated production scheduling helps our firm reduce operational costs by minimizing production delays. | Automated production scheduling improves the utilization of production equipment and reduces operating expenses. | The use of automated production scheduling reduces material wastage and unnecessary production costs. | Automated production scheduling minimizes machine downtime and associated maintenance expenses. | Automated production scheduling contributes to a reduction in the overall operational costs of our firm. |
|-----------------------------------|----------|----------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| N                                 |          | 252                                                                                                      | 252                                                                                                              | 252                                                                                                   | 252                                                                                             | 252                                                                                                      |
| Uniform Parameters <sup>a,b</sup> | Minimum  | 1                                                                                                        | 1                                                                                                                | 1                                                                                                     | 1                                                                                               | 1                                                                                                        |
|                                   | Maximum  | 5                                                                                                        | 5                                                                                                                | 5                                                                                                     | 5                                                                                               | 5                                                                                                        |
| Most Extreme Differences          | Absolute | .635                                                                                                     | .623                                                                                                             | .623                                                                                                  | .623                                                                                            | .659                                                                                                     |
|                                   | Positive | .044                                                                                                     | .056                                                                                                             | .056                                                                                                  | .056                                                                                            | .067                                                                                                     |
|                                   | Negative | -.635                                                                                                    | -.623                                                                                                            | -.623                                                                                                 | -.623                                                                                           | -.659                                                                                                    |
| Kolmogorov-Smirnov Z              |          | 10.079                                                                                                   | 9.890                                                                                                            | 9.890                                                                                                 | 9.890                                                                                           | 10.457                                                                                                   |
| Asymp. Sig. (2-tailed)            |          | .000                                                                                                     | .000                                                                                                             | .000                                                                                                  | .000                                                                                            | .000                                                                                                     |

a. Test distribution is Uniform.

b. Calculated from data.

**Decision Rule:**

Since the calculated z-value (10.457) > critical z-value (.000) at the 5% significance level, we reject the null hypothesis

**Decision:**

Furthermore, comparing the calculated Z- value ranges from  $9.890 < 10.457$  against the critical Z- value of .000 (2-tailed test at 95percent level of confidence) the null hypothesis were rejected. Thus the alternative hypothesis was accepted which states that Automated production scheduling had significant positive effect on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria.

**Discussion of Findings**

From the result of Hypotheses one, the calculated Z- value ranges from  $9.449 < 10.079$  against the critical Z- value of .000 which implies that Automated production planning had significant positive effect on labour cost among pharmaceutical manufacturing firms in South-East Nigeria. In support of the result in the literature review, Knoll (2025) designed and experimentally evaluated a scheduling optimisation approach for a compact end-to-end pharmaceutical manufacturing line, incorporating automated planning of production stages to minimise idle time between processing steps. The findings showed that the automated planning approach reduced the manual

coordination effort previously required to keep production stages synchronised, lowering the labour hours needed to supervise and adjust the line manually. Li (2026), in a study of scheduling efficiency and production costs in a pharmaceutical intelligent manufacturing workshop using an improved particle swarm optimisation algorithm, found that improved scheduling efficiency, achieved partly through automated production planning of batch sequencing, reduced labour costs by 8.1 percent over a six-month period, an outcome attributed to reduced overtime and better-optimised personnel allocation.

From the result of Hypotheses two, the calculated Z- value ranges from  $9.890 < 10.457$  against the critical Z- value of .000 which implies that Automated production scheduling had significant positive effect on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria. In support of the result in the literature review, Miguel et al. (2023) developed a scheduling approach for minimising total completion time in large-sized pharmaceutical quality control scheduling problems, tested against real quality-control laboratory data. Their findings showed that the automated scheduling approach substantially reduced total completion time for quality-control batches compared with existing manual scheduling practice, thereby reducing the operational costs associated with delayed batch release and laboratory idle time. Ouahabi, et al., (2024), in a review of digital twin applications to dynamic production scheduling, found that digital twin-enabled scheduling systems allowed manufacturers to continuously adjust production sequences in response to real-time shop-floor conditions, consistently reducing equipment downtime and the operational costs associated with unplanned production interruptions across the studies reviewed.

## **Summary of Findings, Conclusion and Recommendations**

### **Summary of Findings**

- i. Automated production planning had a significant positive effect on labour cost among pharmaceutical manufacturing firms in South-East Nigeria,  $Z = 10.079$ ,  $p < .05$ . This implies that automated production planning influences how firms allocate employees, organize work schedules, and utilize working hours during manufacturing operations.
- ii. Automated production scheduling had a significant positive effect on operational cost reduction among pharmaceutical manufacturing firms in South-East Nigeria,  $Z = 10.457$ ,  $p < .05$ . This implies that automated scheduling helps coordinate production activities, minimize equipment downtime, reduce material wastage, and ensure the timely availability of resources.

### **Conclusion**

The study concluded that automated production scheduling systems can contribute significantly to cost reduction among pharmaceutical manufacturing firms in South-East Nigeria. By improving production planning, coordinating manufacturing activities, minimizing idle time, and reducing resource wastage, these systems can help firms control operating expenses and improve production efficiency. Therefore, effective adoption of automated production scheduling systems is important for enhancing cost management and maintaining competitiveness in the pharmaceutical industry.

## **Recommendations**

Based on the findings, the following recommendations were proffered

- i. Management of pharmaceutical manufacturing firms in South-East Nigeria should adopt automated production planning systems that align employee schedules with production requirements and available resources.
- ii. Management of pharmaceutical manufacturing firms in South-East Nigeria should implement automated production scheduling systems that coordinate production timelines, equipment availability, material requirements, and workforce activities.

## **Contribution to Knowledge**

This study contributes to existing knowledge by providing empirical evidence on the effect of automated production scheduling systems on cost reduction among pharmaceutical manufacturing firms in South-East Nigeria. It extends the discussion of digital production management by examining this relationship within a specific industrial and geographical context. The findings may also provide practical insights for pharmaceutical manufacturing managers seeking to improve production efficiency, minimize resource wastage, and control operational costs through automated scheduling systems.

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