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Decision support system for handling control decisions and decision-maker related to supply chain

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Abstract

Background: The present study presents a knowledge-based DSS framework for supporting the decision-maker and handling control decisions related to supply chains.

Methods: Two binary variables were adopted for denoting at which time point a given task i starts and finishes. The scheduling issues are represented through the ontological model and appropriately interpreted using the Java environment. Regarding primary data, digital form of administration using google form platform took precedence over physical administration.

Results: The findings might not be exact replication of the findings from previous studies that are limited to the influence of information and material flow on the performance of supply chain as there are concerns of what factors constitute information and material flow that need to be identified and considered. However, with the finding of associating factors of information and material flow may need to consider this in managing the flow and the supply chain. Associating factors such as information quality, information visibility, material cost, fund shortage and so on, play a role in information and material flow and the decisions made in an organization.

Conclusions: Factors associating with information and material flow need to be considered in decision making as well, as the cost in any of the elements affects the flow and this would impede supply chain performance of the organization.

Keywords: Decision support system, Continuous process improvement, Data analytics, Supply chains

Introduction

Information technology supports business activities in fast-flowing information and prompts changes of customer preference era [1]. The recent trend causes a paradigm shift in the production process, which consequently impacts the supply chain flows, with the risk of inefficiency and overexploitation from upstream to downstream. According to Carter and Rogers [2], sustainable supply chains focus on environmental, social, and economic aspects. In this regard, a decision support system (DSS) is emerged from the recent trend and is further competent in supporting the significant issues in the supply chains. Gorry and Scott Morton [3] have initially proposed DSS, and it has been broadly utilized in several realms. DSS aims to support decision-makers in aiding and enhancing their decisions about the process and the consequence of their business functions, which are in the representation of guidance for selecting the optimum sets of options in elevating the profit, customer satisfaction, and efficiency concerning the product.

Extant literature has focused on the use of DSS to support business-related procedures. For instance, these areas include the oil industry, fisheries, marine affairs, environmental sciences, transportation, tourism, and the health sector [4–11]. This pattern indicates a very innovative application of DSS linked with numerous tools and classifications with other approaches for supporting the decision-making process [12]. DSS further experiences criticism when existing and potential consumers do not always take benefit of DSS in supporting their decision-making, either because of the DSS structure or knowledge and awareness. The consumer repeatedly and often utilizes the DSS when the usefulness and easiness are there. Therefore, DSS has to be customized based on problems and activities [13]. DSS has adopted data mining, business intelligence, statistical analysis, and data warehouse. The existing function of DSS is not merely restricted to the database system but also an expert system that aids decision-makers in solving the issues.

The efficacy of DSS is further reliant on the characteristics and construction, specifically in the supply chains, where it requires availability and information for transferring supply and demand between each stratum from downstream to upstream, enabling DSS to aid the decision-maker in the supply chains. There is a broad horizon for developing each decision support system in the supply chains since previous literature has grown significantly in the supply chain realm. Therefore, a knowledge-based DSS framework has been presented in this paper for supporting the decision-maker and handling control decisions related to supply chains.

Literature review

Organizations have always had the development of efficient supply chain systems as their focus. According to Attaran and Attaran [14], collaboration in the supply chain practice is becoming the crux of successful and long-lasting management of business operations. They posited that the inclination to produce quality goods and services is driving up the supply chain cost, affecting the supplier's financial performance. Therefore, the significance of the supply chain to the production and eventual financial strength of the business makes it a top issue for the organization's management [15]. For an organization to run a sustainable and successful supply chain, though, management has to ensure collaborative planning due to its effect on the movement of goods and services. As indicated by Cassivi [16], collaborative planning, forecasting, and replenishment (CPFR) is the bone of the business process that strengthens the management of the supply chain in an organization.

A successful supply chain management goes a long way in benefiting a company in a competition. Some of these benefits are evident in improving the cost of production, distribution, inventory, and the flexibility associated with the 'production of goods and services, and improvement in market share [17] and customer relations [18]. Simatupang and Sridharan [19] posited that flexibility is vital in measuring the success of the supply chain in the organization, and it's one of the benefits of having effective supply chain management. According to Hsu [20], the benefits of supply chain management can be either tangible or intangible. Tangible benefits are exemplified in the cost and reduction of inventory and its effective management. The time saved when the inventory is delivered quickly, while the intangible information accuracy, consistency, flow, service quality, and response time [21]. These, however, can only be realized when there is an integration of various functions and stakeholders in the organization.

According to Stevenson and Spring [22], correct and instantaneous information flow in the supply chain is equally as vital to the business as material flow. "An information-enriched supply chain would have a single customer entity connected to every scheduling process, showing order information flowing to all links, while for a non-enriched supply chain, the customer entity might connect only to the final scheduling link, leaving the remainder of the supply chain hidden from the customer" [23].

Sharing of information is essential due to its reflection of teamwork within the supply chain of an organization [24]. Simatupang and Sridharan [25] refer to information sharing as "the ability to see private data in a partner's systems and monitor the progress of products as they pass through each process in the supply chain; the activity includes monitoring (data capturing), processing, and dissemination of customer data, end-to-end inventory status and locations, order status, costs-related data, and performance status". Simatupang and Sridharan [19] believe that sharing information among supply chain partners allows short time order fulfillment within the order cycle times due to the shared information. Supply chain partners sharing of information generates supply chain information flow management that aids effective decision making among partners. Li et al. [24] stated that information flow is categorized based on the area of operation it is generated and needed. Therefore, the categories of information flow include production plan, inventory, order state, demand forecasting, and sales [26]. In their paper, Koh, Saad, and Arunachalam [27] stated that information flow is needed to support the management of activities like procurement of raw materials, schedule for production, and physical distribution system [28].

For information flow to be complete, two-way communication needs to be conducted, which involves contents, medium/channel, and systems [29]. The content is the actual information to be passed; the medium/channel is the pathway for the information, while the system allows the management of both information and the channel. According to Kembro and Selviaridis [30], information in supply chain information is sharable into three levels within the organization: strategic, tactical, and operational. At each of these levels, different types of information are communicated while various associated advantages and hindrances are encountered in sharing the information in the supply chain. Hsu et al. [31] also separated information shared in the organization into diverse levels, which are: strategic information (e.g., long-term objective, marketing, and customer information) and tactical (e.g., purchasing, operations scheduling, and logistics).

Information exchanged can also be classified into managerial and transactional information. Transactional refers to information required for an organization to conduct procurement or supplies. This class of information is related to payment order, receipt, inventory, transportation, and delivery. This information class relates to the technology needed for operations, quality, costs, and profitability.

From the perspective of supply chain management, information flow and its management are critical activities of the leaders in an organization. The flow of information in the supply chain is bi-directional. This is because other forms of activities, including materials and money flows, are activated by the movement of information to achieve the set objective. This means that material and money flows effective management is positively related to effective management of information flow. Therefore, the huge interest in these flows in literature and supply chain practice is understandable. Several supply chain practitioners have identified the significance of materials flow management as a critical strategic achievement issue [32].

Kuck et al. [33] suggested a data-driven simulation-based optimization approach for dynamic manufacturing system control. The study devised a method for rescheduling production in response to changing circumstances, taking into account aspects that may confuse, such as the simultaneous delivery of many orders. Ersoz et al. [34] attempted to bridge the scheduling theory and practice gap. They tailored their planning operations to the real-time information supplied by the process control and control systems. The dynamic structure of the production environment is quickly sensed in the offered procedure, and the schedule is modified in response to the changing conditions. In manufacturing, the traceability of the parts improved. Furthermore, needless waiting or downtimes were reduced.

Xiong et al. [35] suggested a simulation-based methodology for deciding dispatching rules in a dynamic scheduling issue with task release times and extended technical priority limitations. The proposed approach decreased total delay and the number of late tasks. Zhang et al. [36] conducted a literature study on job-shop scheduling issues and explored fresh viewpoints in the context of Industry 4.0. They added that under Industry 4.0, scheduling issues are addressed using new methodologies and approaches. The findings suggest that scheduling research should focus on smart distributed scheduling modeling and optimization. According to their assessment, this may be accomplished through two methods: combining old techniques and presenting a new way, as well as proposing new algorithms for smart distributed scheduling (Fig. 1).

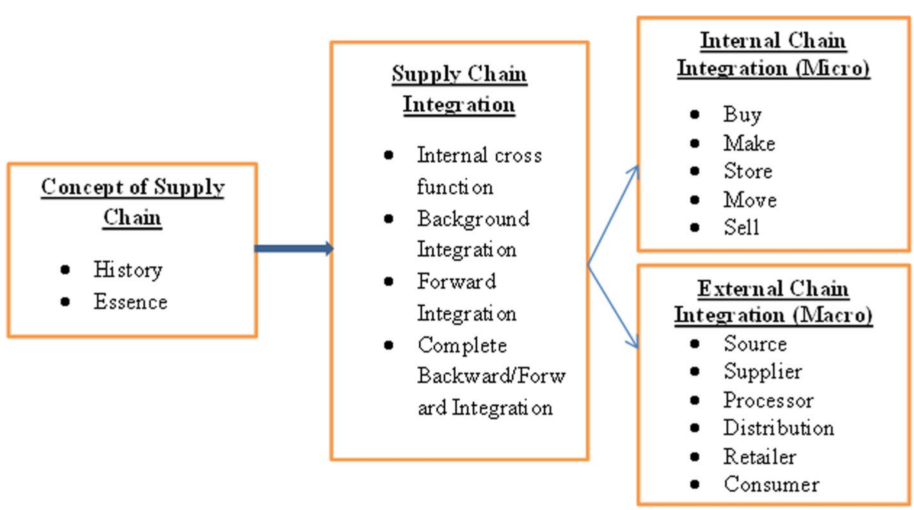

Fig. 1 Supply chain process

In their study, Rossit et al. [37] introduced the notion of intelligent manufacturing that arose with Industry 4.0. They have addressed the subject of smart scheduling, which they feel has a significant role in today's product knowledge. They created the notion of tolerance scheduling in a dynamic environment to avoid production rescheduling. Likewise, Tao et al. [38] investigated contemporary advancements in production systems and smart manufacturing technologies, as well as Industry 4.0 models and stated that dynamic scheduling is one of the significant research undertaken in the literature in the context of Industry 4.0.

Jiang et al. [39] investigated the topic of energy-efficient job-shop scheduling to reduce the total cost of energy use and finishing time. However, the problem at hand was deemed NP-Hard. As a result, they created an enhanced whale optimization technique to address this issue. They improved the whale optimization method by using dispatching rules, nonlinear convergence factors, and mutation operations. They ran simulations to demonstrate the algorithm's usefulness. According to the findings of simulations, the algorithm delivered benefits in terms of efficiency. Ortiz et al. [40] investigated a flexible job-shop problem and offered a novel methodology for solving it. They created a novel algorithm that reduces average tardiness and discovered better solutions than the existing dispatching rules. They developed a real-world production-scheduling challenge and an effective solution for solving it.

Ding and Jiang [41] examined the impact of IoT technologies in an industrial setting. They claim that while IoT has boosted production data, these data are sometimes discontinuous, uncorrelated, and challenging to use. As a result, they devised a strategy for using priceless data. They developed an RFID-based production data analysis system for production control in IoT-enabled smart businesses. Leusin et al. [42] developed a multi-agent system in a cyber-physical approach to handling the dynamic job-shop scheduling problem. The suggested system included self-configuring characteristics in the manufacturing process. This was accomplished through the usage of agents and IoT. In the shop, real-time data was used to make more informed decisions. A real-world case study was used to test the concept. The benefits of utilizing dynamic data and IoT in industrial applications are explored (Fig. 2).

Following a review of the relevant literature, it was discovered that numerous models were created to establish a decision support system for continuous process improvement based on IoT-enabled data analytics. There is a need to improve the decision support system for dynamic settings that can function with various dispatching criteria. The main goal is to improve the efficiency of production management and the job-shop.

Methodology

Knowledge-based decision support systems and model management systems have used tools like artificial intelligence to provide smarter decision-maker support. In addition, a model is presented toward closing the gap between analytical and transactional models, which are utilized in the organizational and technical aspects. It further implements different hierarchical levels throughout the enterprise structure, making information quality available. In particular, different and multiple decision insights might be sufficient throughout the decision-making task, which increases the speed response of the decision-support system.

	What information is shared	Benefits of information sharing
Operational level	• Order information • Delivery schedule	• Supporting the daily physical flow of products through the supply chain
Tactical level	• Forecasts of the production within next 12 weeks • Monthly meetings	• Attempt to predict and match supply with demand in distribution to better synchronize production and logistics capacities
Strategic level	• One-year demand forecasts and production changes • Five-year plans concerning planned expansion and required investments • Joint business plan	• Strengthened relationship and increased trust between partners • Shared view of the future and potential growth to ensure that sufficient production capacity is available

Fig. 2 Supply chain planning using DSS

This study tackles process control decisions associated with coordination and procedural control. Thereby, the integration of control sequence steps in the equipment modules is dealt with along with the transition between control recipes. Such decisions are mentioned in the control aspects, which receive data from the scheduling point, and offer data with the actual phase. Afterward, the information flow procedures were presented at this decision level and their association with other decision levels. The decisions are associated with the integration of the control recipe. The batch operation is managed through coordination control using the control recipe scheme in the ontological model. MATLAB managed data, and the JAVA environment offers the control function from the scheduling function with the relevant data. Consequently, it is an iterative process for decision-making, which encompasses the scheduling and control levels.

Moreover, the continuous-time STN illustration relies on explaining a common time grid that is variable and authentic for all shared resources. The model implies that all tasks commencing at a predefined time guarantee the authenticity of the material balances. Two binary variables were adopted to denote when a given task starts and finishes. The scheduling issues are represented through the ontological model and appropriately interpreted using the Java environment. GAMS implemented the formulation, whereas MILP solver was utilized to execute this formulation as the implied issues were lineal.

Concept integration

The DSS framework is intended to aid in the decision-making process. Many alternatives exist, particularly those linked with Industry 4.0 technologies; nonetheless, researchers' objective is to build a more robust system to reduce the risk of human mistakes, particularly during the data entry phase. However, the critical components of DSS and technology employed are data management, communication, the user (decision-maker), and the simulation model. The Knowledge-Based Engineering (KBE) technique was used to create the framework, which is ideal for lean products. Furthermore, knowledge in DSS and Industry 4.0 indicates the use of data management tools via IoT in this idea where human aspects (users/decision-makers) continue in developing innovation to boost productivity (Prasad, 2014) (Fig. 3). In conjunction, LM principles functioned as a bridge.

Developing framework

Combining physical and virtual processes results in smart manufacturing (Godfrey, 2002). IoT uses the internet networking idea to collect data from sensors. The data is collected using a barcode sensor. They are then installed in the database before being sent to the server through the network. The MySQL command is provided to compile and code the data to match the simulation required input. These step procedures give the core of an Industry 4.0-compliant networking system. Simulation-based Knowledge-Based Modeling (KBM) allows users to forecast and produce reliable results based on simulation data (Prasad and Rogers, 2005). Figure 4 illustrates the enhancement of proposed system in the context of Industry 4.0.

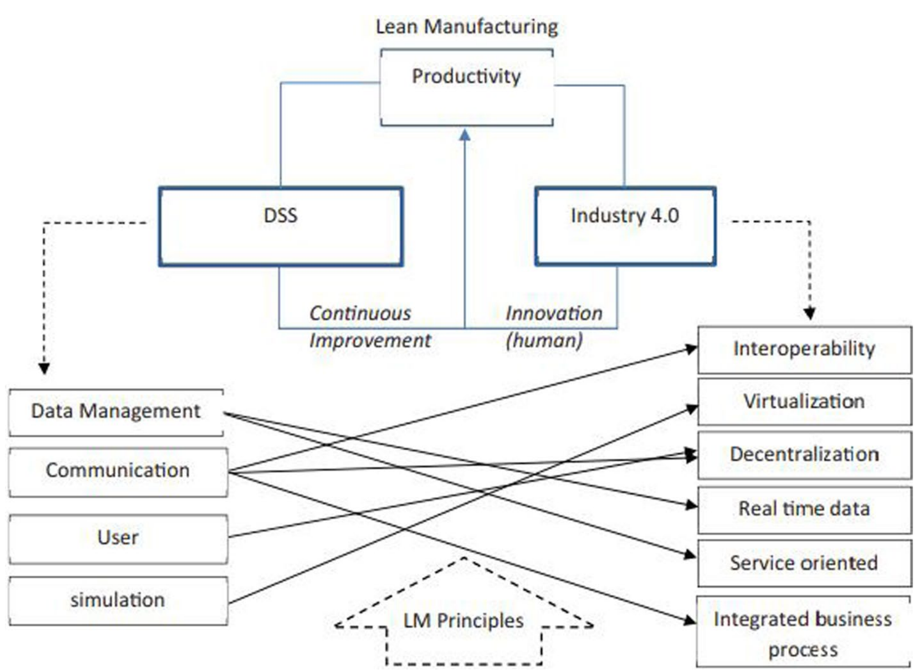

Fig. 3 Concept of DSS design based on KBE (Source: Prasad, 2014)

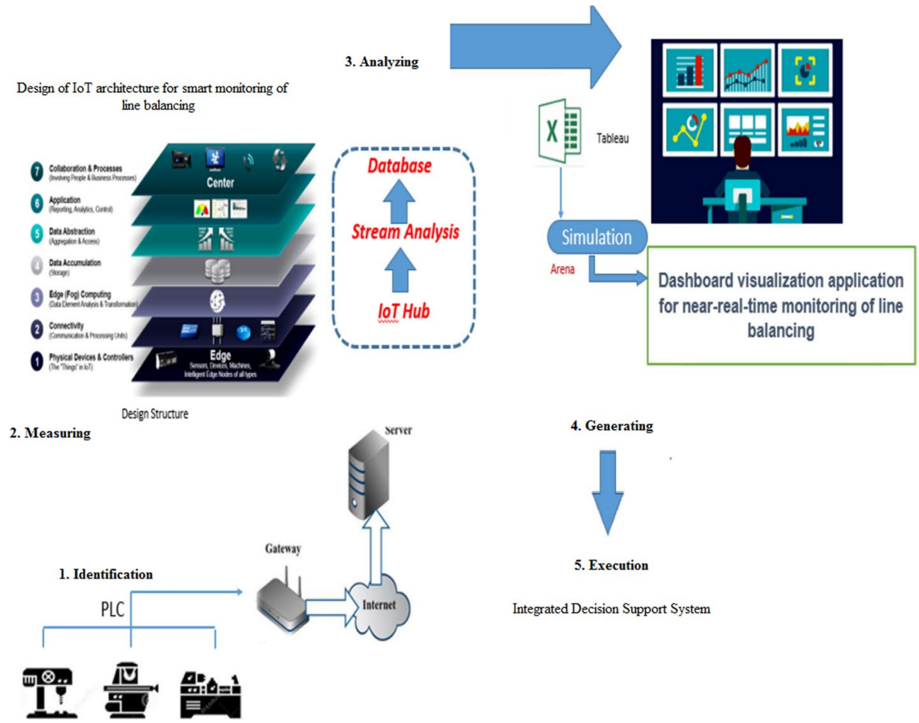

Fig. 4 The proposed framework

Data requirement

The data needed are specified to take decisions at the scheduling level. The phases consist of the usability to schedule predefined in this ontological model regarding all cases. In particular, the scheduling function needs the information regarding capacity, demand, due date, product stage-unit, quantities in/out, processing time, stage-process, time horizon, and unit availability. The Java code was programmed to generate the input files to schedule optimization tools.

The investigation is made for academic purposes only and not for the organizations' promotion or human resources appraisal. The questionnaire was e-mailed to the respondents along with a consent letter which doubles as a letter of introduction of the research and what is expected of the participants. Participants were assured of their anonymity and the confidentiality of their responses. The participants were also assured that no harm would befall them on their participation in the study. The participants were informed to fill and submit the form online only if they were interested in participating in the study. Otherwise, they were imploring to ignore the mail. The responses from the participant were downloaded after a couple of weeks of initiation, and the result was analyzed. The study also searched online, via the Google search engine, for articles related to information and material flow in organizations published in reputable journals, reviewed them for collation of data on associating factors of information and material flow. The result of the review formed the basis of identifying factors related to information and material flow for the study.

Data administration

Data collected from the company staff were subjected to analysis using SPSS v20.0. Descriptive statistics, factor analysis, correlation, and regression tools were used to analyze the data. Factor analysis was done to illustrate the strength of items or associating factors of information and material flow and supply chain performance in their groups. The correlation was used to test the relationships between information and material flow and supply chain performance. On the other hand, regression analysis was deployed to understand the predictability of information and material flow of supply chain performance and which of the independent variables has a stronger contribution to supply chain performance.

Results

The descriptive analysis explains the percentage distribution of the respondents on the characteristics of the demographic variables (Table 1).

The result of factor analysis of the data collated from the sampled organizations is presented. Factor analysis is the calculation and explanation of the strength of individual items concerning the group that forms the whole of the factor being investigated.

Table 1 Descriptive statistics

Age	Frequency	Percentage	Valid percentage
20–30 years	5	5.0	5.0
31–40 years	21	21.0	21.0
41–50 years	52	52.0	52.0
51–60 years	22	22.0	22.0
Total	**100**	**100.0**	**100.0**
Educational qualification	**Frequency**	**Percentage**	**Valid percentage**
Ordinary national diploma	2	2.0	2.0
Bachelor's degree/higher national diploma	39	39.0	39.0
Master's degree	58	58.0	58.0
Ph.D	1	1.0	1.0
Total	**100**	**100.0**	**100.0**
Work Experience	**Frequency**	**Percentage**	**Valid percentage**
1-5yrs	13	13.0	13.0
5-10yrs	56	56.0	56.0
11-15yrs	29	29.0	29.0
16-20yrs	2	2.0	2.0
Total	**100**	**100.0**	**100.0**
Level in the organization	**Frequency**	**Percentage**	**Valid percentage**
Director	3	3.0	3.0
Senior Manager	31	31.0	31.0
Middle Manager	62	62.0	62.0
Non-managerial level	4	4.0	4.0
Total	**100**	**100.0**	**100.0**

Table 2 Varimax rotation

Information flow items	F1	F2
(1) Information quality in the form of disaggregation—Quality information is exchanged between supply chain partners in the organization using a disaggregation information system	0.948	159
(6) Visibility—Supply chain partners of the organization have visibility on information related to material demand and supply for decision making	0.895	0.075
(2) Accuracy—Information is accurate and flows seamlessly in the supply chain network for all partners of the organization to use in making decisions	0.890	0.083
(4) Information credibility—Information flow in the organization is credible and based on trust and commitment among the supply chain partners	0.872	0.241
(3) Information adequacy—Information and the infrastructure required for information flow in the organization is adequate	0.858	0.056
(5) Information timeliness—Adequate information is shared promptly between supply chain partners of the organization	0.776	0.024
Material flow items	**F1**	**F2**
(1) Material price fluctuation is a primary concern in the organization as the cost of material in one area affects the cost in other areas such as logistic	0.047	0.899
(7) Unnecessary paperwork—Technology helps reduce unnecessary paperwork in managing material flow and supply within a given supply channel of the organization	0.088	0.896
(5) Fund shortage—Inadequate financial strength delivers a burden and risk to material flow between parties in the supply chain collaboration of the organization	0.123	0.893
(8) In-house logistic problem—Direct material flow through process turnaround time and in-house logistics is effective in the organization	.079	.871
(3) Delivery delay—material flow is not a concern in the supply chain as the organization effectively manages products delivery to customers promptly	0.060	0.857
(2) Imperfect sorting—Imperfect sorting is a recurrent phenomenon of slow and uncoordinated sorting that disorganized material flow in the supply chain in the organization	0.207	0.776
(4) Poor planning—Poor coordination in planning is a significant concern that hinders material flow in the organization	0.214	0.524
(6) Non-alignment specifications non-alignment specifications in design and coordination of materials flow from supplier to manufacturer and finished		

Table 3 Rotated component matrix for supply chain performance

Product flexibility (F1)*items	F1	F2
(3) Improve the volume changes	0.898	0.084
(2) Improve the adjustment of the capacity	0.895	0.082
(1) Improve product variety	0.848	0.458
(5) Improve product mix	0.824	0.157
(6) Improve the rapid design changes	0.786	0.034
(4) Improve product features	0.775	0.342
Product delivery (F2)*items	**F1**	**F2**
(1) Improve the response time to demand changes	0.055	0.896
(4) Improve the accuracy of the predictability of delivery dates	0.0798	0.873
(3) Improve speed of delivery relative to competitors	0.213	0.865
(2) Deliver the kind of products needed	0.074	0.736
Eigenvalue	4.389	3.645
Percentage variance (73.87%)	29.628	24.672

Table 4 Correlation analysis

Variable	Mean	SD	1	2	3
Information flow	19.53	1.98	–		
Material flow	27.06	2.61	0.78	–	
Supply chain performance	38.40	2.96	0.237*	0.411**	

* significant positive relationship (information flow & supply chain)

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Table 5 Regression analysis of information and material flow on supply chain performance

Variable	Coeff (β)	Std. error	t-Statistic	Prob
Information flow	0.423000	0.054000	4.534000	0.0000
Material flow	0.523000	0.046000	5.648000	0.0000
R-squared	0.54000	F-statistic	31.236	

Tables 2 and 3 present the strength of things that make up information and material flow and supply chain performance within organizations.

The primary data quantitatively obtained from the sampled organization was used for the analysis due to its validity in evaluating the extent of information and material flow and level of supply chain performance in the organizations. Correlation analysis explains the relationships between information and material flow and organizations' supply chains. On the other hand, regression analysis illustrates the strength of the contribution of information and material flow on supply chain performance to explicitly ascertain the causal association in line with the third objective of the study. The correlation and regression analysis results are presented in Tables 4 and 5.

Table 4 presents the correlation matrix analysis showing the inter-correlation between information flow, material flow, and supply chain performance. First, the table shows the mean of Information flow to be (M = 19.53; SD = 1.98); Material flow (M = 27.06; SD = 2.61); Supply chain performance (M = 38.40; SD = 2.96). The relationship between the variables shows that there are significant positive relationships between information flow and supply chain performance (r = 0.237*). Also, the result in the table shows that material flow is significant in its positive relationship with supply chain performance (r = 0.411**). This result implies that the less hampered the flow of information and material experienced, the higher the level of supply chain performance. To get a clearer picture of each of the information and material flow and their strength of prediction supply chain performance, the data is further subjected to regression analysis, and the result is presented in Table 5.

Table 5 presents a regression result showing the relationship between information and material flow and supply chain performance. Recall that the elements of information flow considered in the study are: information quality, information accuracy, information adequacy, credibility, information timeliness, and visibility. The elements that makeup material flow include material price fluctuation, imperfect sorting, delivery delay, poor planning, fund shortage, non-alignment specification, unnecessary paperwork, and in-house logistic problem. The result showed that material flow represents the strongest factor in predicting supply chain performance. It had a significant positive relationship and accounted for about 52.3% of the variance of supply chain performance (Beta = 0.523; t = 5.648; pv = 0.000). Information flow also had a significant positive relationship, but account less for about 42.3% of supply chain performance (Beta = 0.423; t = 4.534; pv = 0.000). Collectively, information and material flow had a significant positive relationship of 54.0% with supply chain performance of organizations (R2 = 0.540; Fcal = 31.236; pv = 0.000); although there is a significant difference in the degree of contribution of the individual factors to supply chain performance as pointed out by the Fcal.

Data mining techniques can process the data present in dynamic databases to determine the problems faced in production, generate rules to control output, improve product quality, and develop automation based on work intelligence. A better understanding of production systems may aid researchers in developing sophisticated DSS and decision-makers in making better judgments. Controlling the production environment with real-time data may also assist researchers in modeling the system without making any assumptions. This technique can bridge the gap between theory and experience, resulting in more realistic solutions.

Furthermore, real job processing times might be validated using job data from the past. This study would aid in predicting the system's behavior under various scenarios, any subsystem could simply integrate into this system. Combining artificial intelligence or machine learning-based subsystems might form the basis of future smart factories. In this regard, this study indicates the benefits of such subsystem integrations, such that even technology integration in a real job-shop may take considerable time and effort.

Conclusion

The findings might not be an exact replication of the results from previous studies that are limited to the influence of information and material flow on the performance of the supply chain as there are concerns of what factors constitute information and material flow that need to be identified considered. However, with the finding of associating information and material flow may need to consider this in managing the flow and the supply chain. Associating factors such as information quality, information visibility, material cost, fund shortage, and so on, play a role in information and material flow and the decisions made in an organization, which in turn impact supply chain performance, as cost of material, for example, significantly impact the flow of materials. Factors associated with information and material flow need to be considered in decision making as well, as the cost in any of the elements affects the flow, which would impede the organization's supply chain performance. As a supply chain involves a network of supply chain partners, organizations need to ensure that information quality, information visibility, material price, funding, and so on are managed effectively through a centralized policy as they provide significant insights into the health of the supply chain.

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Authors' contributions
DHA: analysis & drafting. AAJ: conception, administration, analysis, editing & approval. Both authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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