# INVESTIGATION ON DECISION SUPPORT SYSTEM (DSS) IN LEAN MANUFACTURING INDUSTRY FROM BEHAVIOR AND TECHNICAL ASPECTS

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***ABSTRACT***

*In every industrial enterprise, choices are crucial since they may decide success or failure. Consequently, the decision-making process is crucial to lean production. However, further study is necessary to appreciate the relevance of Decision Support System (DSS) in the lean manufacturing business. This study exposes the classification of DSS, its range of applications, and suggestions for future research based on two key factors, namely, behavioral, and technological problems. This study makes considerable use of academic databases such as Scopus, Google Scholar, Emerald Science, and ResearchGate. In total, 50 papers have been identified. Each result, criterion, and categorization are supplied and classified. It is proved, from the literature treasure that DSS has the highest contribution on the Evaluation, 38%, following by, Mixed Application 26%, and others. Henceforward, this paper discussed the Behavior Aspects of users' confident, prejudice and discrimination issues, and customization. From the Technical issues, the discussion was on the technological capabilities, software language, parameters aggregate, user interface, market culture and social norm, giving out criticism for the future development of DSS-Lean, especially for the manufacturing industry. The authors believe that this study will lead the way for future research in the same field based on its primary findings.*

***Keywords:*** *decision support system, lean manufacturing, behaviors aspects, technical aspects*

## 1.0 INTRODUCTION

A decision is a judgement or conclusion made after weighing several factors (Forsyth 1992). The complexity and unpredictability of the decision-making process have heightened the need for research on Decision Support System (Simões-Marques et al., 2022) and (Braun et al., 2021). According to Abd Rahman et al., (2021) and Ito et al., (2020) the decision-making process has become a daily issue for the industrial sector as a result of several operational needs, and the growth of Information Technology (IT) enables the implementation of a computerized decision-making system. Consequently, decision support systems play a significant role and are becoming an integral part of industrial investment selection operations, assisting decision makers at all levels of manufacturing management (Abd Rahman et al., 2020). Nonetheless, Chiu et al., (2022) and Reyes et al., (2021) state further research is required to understand the behavioral and technological components of DSS development that are customized for lean manufacturing. Lean manufacturing is a method to production that aims to maximize output while decreasing waste in manufacturing processes (Kumar et al., 2022). Everything that does not give clients with value for which they are willing to pay is considered waste according to the lean mindset (Kumar et al., 2021). Nevertheless, Ismail (2008) has sorted the waste into procedures, activities, objects, and services that demand time, money, or expertise but provide no consumer value. These may include latent talent, surplus inventory, inefficient or wasteful procedures and processes (Bhat et al., 2022). This research was prompted by the following questions:

1.1 What is the DSS characters that mediates the link between lean manufacturing (LM) and DSS?

1.2 How does DSS effect lean performance and productivity?

1.3 What are the critical gaps for future behavioural and technological recommendations?

## 2.0 METHODOLOGY

This technique of investigation consists of a series of processes, starting with data collection and going through information analysis, theory development, establishing of reasonable reasons to believe, and consensus-based conclusion. If a work analyses the incorporation of DSS into lean manufacturing processes, it is pertinent into this investigation. In addition, the papers must be written in English and include relevant data to support the application's results. This assessment does not include research articles that just give conceptual models without validation. In addition, conference papers, doctoral dissertations, textbooks, master's theses, and review articles were deleted to offer a fair picture of the application of DSS to the manufacturing industry. As shown in Fig. 1, the researchers adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standard.

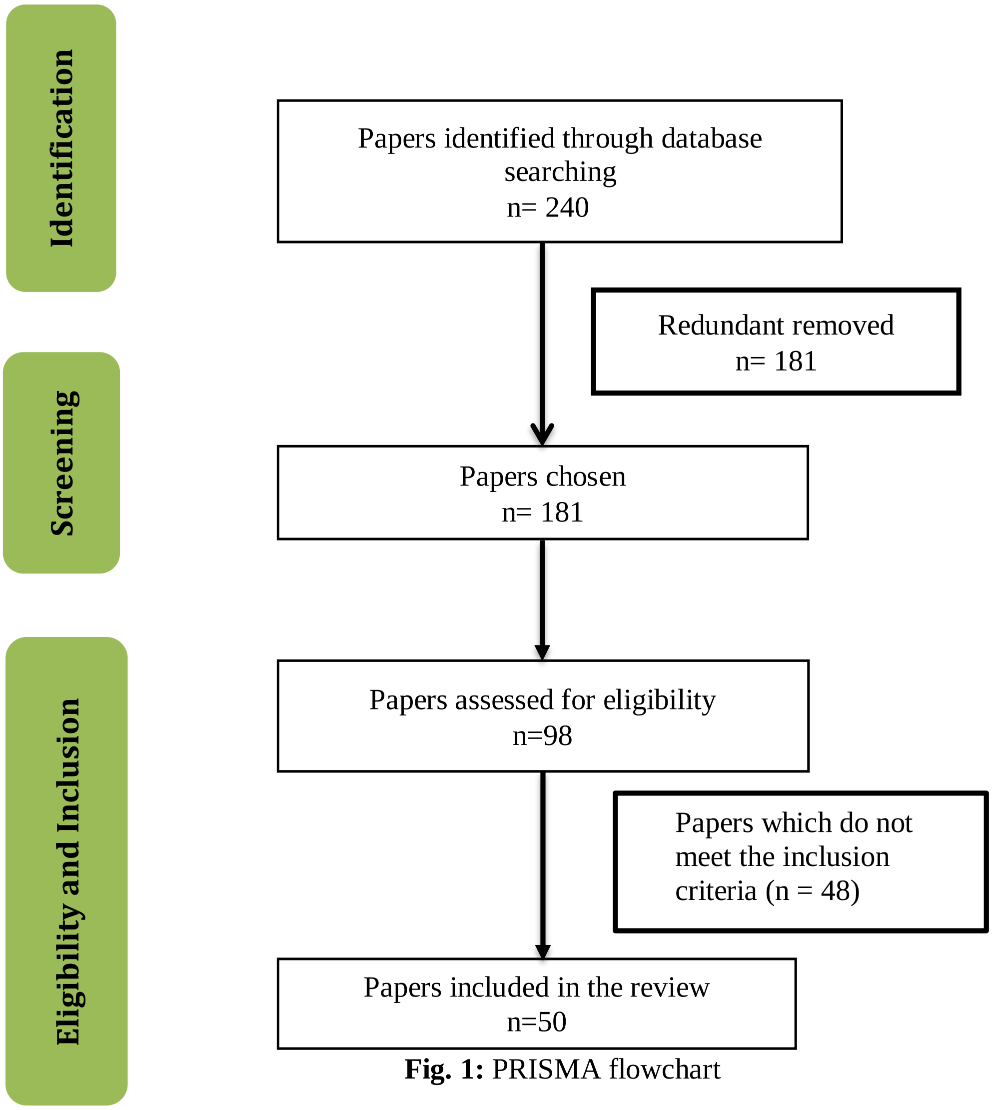


**Fig. 1:** PRISMA flowchart

## 3.0 FINDINGS AND DISCUSSION

### 3.1 The DSS Characters that Mediates the Link between Lean Manufacturing (LM) and DSS

DSS was introduced in the middle of the 1960s and is described as computer software that enhances individuals' or groups' decision-making abilities and is backed by an automated data system (Al-Rahmi et al., 2019). On the other hand, Mufana and Ibrahim (2022) has concluded that DSS is a unified, robust system that supports three kinds of decision-making processes, encompassing structured, semi-structured, and unstructured issues, as well as data, advanced analytical tools, and user-friendly software. DSS has also been defined as a system that improves the process and output of decision-making or increases the quality and efficacy of proposed resolutions, as well as for the application of diverse data and models to human-machine interface (HMI) to assist decision makers at all levels of conflict (Koumas et al., 2021). Complementing this, Bumblauskas et al., (2017) emphasizes that DSS is a computer-based information system meant to facilitate the making of complex choices via a more in-depth and concentrated assessment of the topic at hand. Providing decision assistance to all levels of management to permit any development, being readily customizable and user-adaptable, and being either a standalone system, an integrated system, or a web-based system, according to Jørgensen and Nissen (2022) and Virkar et al., (2022). DSS facilitates individual, group, and team decision-making, as well as several independent and interdependent options. In addition, DSS must be capable of modelling "What if?" scenarios that produce reliable projections of the future. DSS consists of several mathematical, statistical, and operation research models. The most crucial of the listed requirements is that the system should assist the decision-maker rather than replace human throughout the process (Wang et al., 2022). Supporting this, Saba et al., (2021), has stated that despite the issue's high level of intricacy, DSS is unable to exert complete control and prevent influencing the next judge's judgement. As according to Chandran et al., (2022), the major components of DSS are the data warehouse, software system, and conversation manager. However, the question of whether aspect of DSS mediates the relationship with lean remains. According to Antosz et al., 2011), there are three fundamental types of DSS: Data-Driven, Model-Driven, and Knowledge-Driven as shown in Figure 2 below. In the analysis of this issue, it is clearly discussed that each of the three DSS classes has its own operating system, but that in the lean manufacturing, all three are combined to form the compound-oriented DSS which enables users to easily generate, evaluate, and modify data even due to the versatility of data analysis, the decision chosen may also be resolved more efficiently.

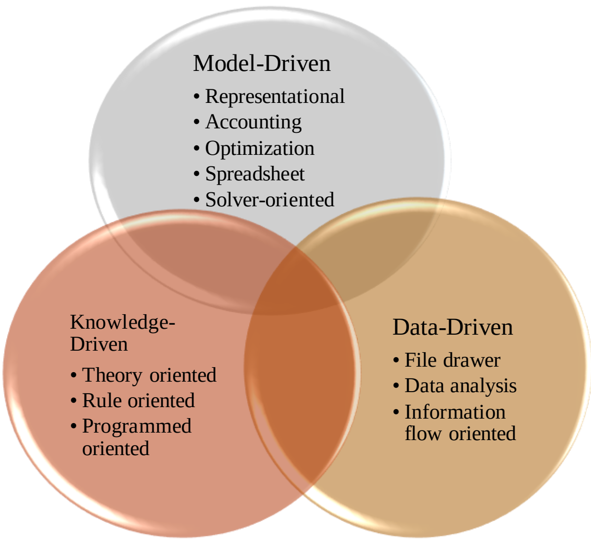


**Fig. 2:** DSS classification (Antosz et al., 2021)

Finlay & Forghani (1998) has classified the DSS into three classifications: (i) data-driven, (ii) model-driven, and (iii) knowledge-driven. Table 1 below explains every classification.

**Table 1:** DSS Classification

| Classification | Description |
|---|---|
| Data-driven (Sai et al., 2019) and (Manickam and Rathinasamy, 2022) | This system focuses on the access and administration of enormous datasets, such as internal or external time series and external structured data. |
| Model-driven (Bertoni et al., 2021) | Each created model-driven DSS serves a unique purpose and has its own set of obstacles. It promotes model access and manipulation. Analytical models, such as accounting and financial models, representational models, and optimization models, make up the majority of the system. In addition, it does not need a huge database since user-supplied data and settings are used. |
| Knowledge-driven (Yang, 2022) | Knowledge-driven DSS assists decision makers by suggesting an appropriate solution to an issue based on its problem-solving expertise. This problem-solving capability of DSS is made possible by the incorporation of artificial intelligence. This system uses inference engines, such as a heuristic model, to process the rules. |

### 3.2 The Effect of DSS on Lean Performance and Productivity?

The research then investigates the application of DSS in lean manufacturing to see how DSS affects lean performance and productivity. This study divides the fifty papers collected on DSS applications into six distinct categories: Evaluation, Prediction, Selection, Optimization, Scheduling, and Mixed Application. 38% of Fig. 3 indicates that Evaluation is the primary aim of DSS for lean manufacturing. Then, 26% of the published literature covers Mixed Application with DSS. 18% and 8% of papers are devoted to Optimization and Selection, respectively. The least mentioned objectives are estimation and planning, with 6% and 4% mentions, respectively.

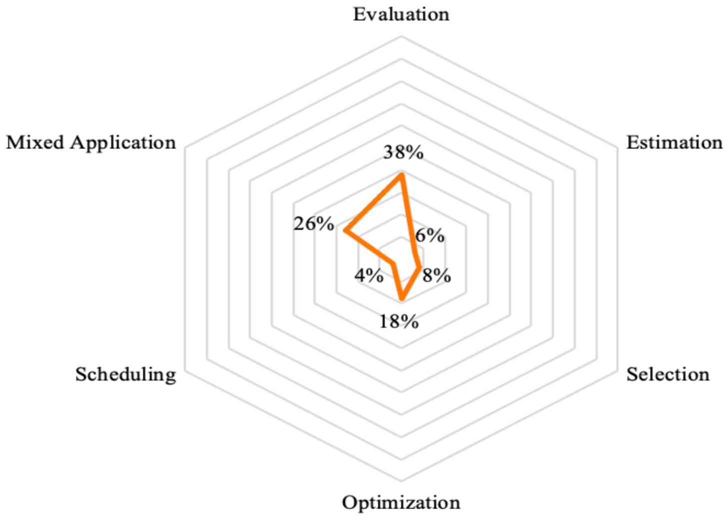


**Fig. 3:** The DSS Application on Lean Manufacturing

Su et al., (2023) indicates that, for assessment purposes, DSS will examine the technical hurdles of changing blockchain technology via the construction of fuzzy entropy-rank that employs algorithm consensus and computer paradigm. Another example of a DSS application for assessment is performance evaluation, which aimed to design a decision support system (DSS) framework that connects Andon and simulation using Internet of Things (IoT) idea. The findings imply that digital factories may use the DSS with relative ease to support planned and operational operations (Peña et al., 2022). Introduce an Anticipative Plant-Level Maintenance Decision Support System that gives advice on corrective and preventive maintenance priorities based on the equipment bottleneck rankings with the goal of enhancing daily plant throughput (Guner et al., 2025).

For the purpose of prediction, DSS has also been applied to the production transformation, with an emphasis on connective mechanisms and platforms that employ data analytics from the real world, by proposing a theoretical framework that integrates lean, data analytics, and the (IoT) to improve the entire production process. Using the Internet of Things and data analytics in simulation to reduce bottleneck issues by adhering to the lean philosophy (Ito et al., 2020). In a separate body of research, DSS is constructed for the job allocation mechanism in order to identify several choices for incorporating robots into the assembly line to do various duties. Using a decision support system based on the HUMANT algorithm, the choice representing the best compromise solution was chosen. The process is experimentally evaluated on the production line using genuine automobile gears (Gjeldum et al., 2021).

DSS also supports industrial optimization activities. Recent study, Psarommatis and Kiritsis (2022) developed a DSS that helps cost optimization work by reducing manufacturing time via the use of fused deposition modelling technology. This study focuses on detection and repair-based strategies. It uses a newly developed hybrid Decision Support System (DSS) that combines data-driven and awareness approaches to identify issues and then automates the necessary decision-making procedures. The system leverages an ontology based on the ontology to describe the production domain and provide contextual information to available data. Real-time production data and historical data are used to analyze issues, evaluate their type and severity, and provide alternative repair alternatives. Using a dynamic, multi-criteria assessment technique, more research is being conducted that aids the engineers' selection of the ideal manufacturing process solution by identifying the repair plan best suited to the current production conditions. In addition to facilitating cost minimization, developed DSS may assist operation optimization (Kocsi et al., 2020).

In addition to concentrating on a single application, DSS has also been designed to support many apps simultaneously. This study has developed a DSS capable of assessing the current manufacturing performance in terms of lean readiness and projecting the future relative cost of lean deployment. DSS may also aid in the evaluation and selection of several choices, such as the selection of equipment, machinery, or software (Liebrecht et al., 2021).

## 4.0 THE CRITICAL GAPS FOR FUTURE BEHAVIOURAL AND TECHNOLOGICAL RECOMMENDATIONS

In this section, the researchers address the study topic of what the most significant information gaps are for future recommendations from a behavioral and technological standpoint. The study focuses on issues linked with the development, deployment, and use of DSS in the industry. The data extraction is divided into two primary categories: behavioral and technical inquiries. The purpose of this categorization is to address the outstanding problems associated with the existing application. This study is concerned with the development of quantitative models, the storage and retrieval of data required by various models, parameter communication among models, multi-participant interaction in model use and value elicitation, the impact of user interface design alternatives, and the effectiveness and usability of the resulting systems. However, this investigation also examines the issue of designing, implementing, and using the present DSS.

### 4.1 Behavior Factors

This section concentrated on deportment and etiquette of the DSS users, with the main aim to commiserate with behavioral impact received from DSS. The questions are answered based on the literature identified relevant to prior research.

#### 4.1.1 Are users of a framework DSS more likely to accurately apply the findings if they comprehend the model? Once they comprehend the model, do they use it more often? Do they now have more confidence in the outcomes? When users comprehend a system's model, does this promote improved decision-making?

Based on the findings of the empirical investigation, insufficient research has been conducted on the topic at hand. No research could reach the conclusion that DSS improves decision-making. Rather, it is crucial to conduct meta-studies that include the contingency elements, such as the users' grasp of the underlying models in the previous DSS model.

#### 4.1.2 Some users may attempt to modify model parameters using "what if" to produce an unclear forecast. If this is the case, what kind of persons are more likely to exploit the "what is" manipulation?

The perspective gleaned from this study is that prejudice resulting from "what if" scenarios is frequent among users seeking the quickest and most preferred response based on personal desires. The reason for this is because, according to Saeed et al., (2020) the nature of providing the future forecast to the users makes it easier for them to divert from the choice that must be made based on their particular preferences. This view is reinforced by the behavioral choice theory by Tusche and Bas (2021) which examines the social, emotional, and cognitive processes that individuals use to perceive and choose between options. Thus, in future DSS should consider the decision-values, user beliefs, and preferences that are definitely impact the decision-making processes.

#### 4.1.3 Which circumstance will be affected by the prejudice made? Will other solutions avoid the discrimination?

Research pertaining to the elicitation of subjective probabilities and values indicates that debiasing is possible and that certain elicitation approaches give normatively superior outcomes than others (Zellner et al., 2021). The eliciting values, including those on eliciting subjective probability, have relied on non-computerized solution such as the short-term diversity training whereby providing the users on the exacerbated by overt conflict within the organization. This strategy is used to reduce the influence received from the prejudice arise as stated by Bianchi et al., (2021). In addition to this, intergroup dialogue programmed combined with conflict mediation resolve-technique are also being suggested by this paper as the discrimination is reduced by improving the tolerance and miscommunication as well as positive relations against the negative stereotypes Badaan and Jost (2020). More study must be conducted on the elicitation of values since it may affect the effectiveness of DSS.

#### 4.1.4 Does user interface influence the use of DSS framework? What level of "customization" is required and feasible for this extent?

Web portal and other Web interface personalization are typically viewed as desirable Serrou and Abouabdellah (2016) and Mansyur et al., (2011) have culminated that, because DSS users vary individually, a personalized interface would increase a DSS's usability, frequency of use, and effectiveness. This field of study must be reconsidered within current technological developments.

#### 4.1.5 What effect does DSS in a "very realistic" simulated decision environment have on a person's decision making in the "real" decision environment? How can simulation be used more effectively to evaluate the effects of alternate predictions on decision methods and policies?

The effect discussed in the literature collected are, among others, Pomarlan and Bateman (2020), has discussed that simulation helps in learning more about the modelled system, providing tools for experimentation and behavior prediction, answering questions like "What would happen if...?" and providing answers to these questions. Simulation makes it possible to compare systems' performance in various scenarios and to comprehend how systems react over time. Additionally, simulation models enable the examination of complicated systems that are not amenable to representation by analytical models (Zhao et al., 2020). Moreover, the simulation in future should adapt the philosophy existed such as, the lean system, in order to have a clear insight on the prediction made. This will enhance the evaluation of the effects coming from alternate predictions on decision methods and policies. Nevertheless, the adaptation will enlarge the ability to experiment various alternatives and assess the outcomes within the systems' scope, where doing real experiments would be expensive, time-consuming, or dangerous.

### 4.2 Technical Factors

While attempting to study and interpret fresh data as knowledge novelty, there are extra challenges brought on by the exponential expansion of technology giving the fundamental theory for future evolution as a result. The relevant technical concerns have not been resolved explicitly, nor do they seem to be effectively handled in the present body of literature. Thus, the authors would like to discuss several issues regarding the technical factors in DSS development according to the questions created below.

#### 4.2.1 What technological capabilities are required for the development of the future generation of DSS, particularly for the creation of real-time DSS?

As of late, firms generate vast quantities of data and consume information to create knowledge and, eventually, the best choice. It is anticipated that data consumption will provide the ability to monitor, evaluate, and track corporate progress. However, as data grow more pervasive, digitalization has become the primary data management strategy. To accelerate decision-making, the next-generation DSS must include an operational framework that can turn data from current sources and analytics into new types of knowledge and information (Härtel and Härtel 2020). The subsequent component is security as to what emphasize by Lam et al., (2025) which guarantees that all submitted data is preserved safely and that no competitors have access to the company's secret information. Compliance implies as according to Jiang et al., (2019) that the DSS produced must correspond to certain regional and industry norms. For example, the employed server must adhere to the typical needs of the users.

The next idea is synchronous as to what has been discussed by Agrawal and Narain (2021) which maximizes production efficiency by synchronizing data with information flow and process execution throughout the value chain. Whereby, agile commoditization facilitates swift decision-making, providing an instant support for the business process. Additionally, the DSS should be very adaptive since current delivery systems are expanding more rapidly than fundamental traditional business operations Cleary and McLarney (2021). As example, to allow individuals total control, it must also be virtual. In addition, it is recommended that the DSS adopt a service-oriented approach as discussed by Bagnoli et al., (2022) and Gattornaand Ellis (2019) to enable task-centric workflows, as enterprise solutions as opposed to application silos, customization as opposed to standardization, incrementally built, and deployed as opposed to drawn-out development cycles, built to last as opposed to change, and distributed federated model as opposed to centralized governance model are the guiding principles.

### 4.2.2 Which software capabilities are optimal for implementing DSS? How do they respond to the abundance of information?

According to Gjeldum et al., (2021) there are six features of software capabilities: social networking, document management, a powerful search engine, task management, an intuitive user interface, and a security mechanism. The improvement of these five features is essential to increase the DSS's efficacy by offering a platform for knowledge exchange, data analysis, and document archiving, and most crucially, the resolution of particular business issues. With the incorporation of collaborative communication technologies such as chat, desktop sharing, whiteboarding, voice exchange, and live-video conferencing, it has been demonstrated that the software capabilities have effectively addressed the issue of information overload in this richer media environment where billions of data are transferred simultaneously (Yurin et al., 2018).

### 4.2.3 Is a certain 'language' required for data to communicate across parameters?

The word 'language' refers to a fundamental text-based format for conveying structured data, including documents, data, configuration, books, transactions, and invoices (Udokporo et al., 2020). This paper suggests a Markup Language (ML) in which is a specialized language that differentiates various document kinds within the same systems. ML identifies multiple structures by giving "tags" to data pieces that indicate their name and format. By using a common identifying structure within the system, data may be readily transmitted across diverse systems, up and down agency levels, across the nation, and globally over the Internet. Sawrav and Bandyopadhyay (2022) found that ML offers the technological foundation for interoperability and is compatible with the most common Internet transmission protocols and is highly compressed, allowing for a faster transfer rate as backed by Nurnazar and Atabek (2021). To support this stand, according to Bernardo et al., (2020) and Tang et al., (2021), the majority of large software developers have fully accepted the ML standard, and while ML is relatively intuitive for developers, even non-ML specialists can understand the ML file.

### 4.2.4 Is aggregate important for the parameters emerging? And act as technological infrastructure in achieving the model desired?

As stated by Li et al., (2021) aggregating is a sort of relationship in which model elements are constructed or adjusted to generate a more complex item. In addition, it presents a mechanism for merging the parameters of all software development models. Aggregation also protects the integrity of interconnected projects that are sensitive to any changes or directives that may impact the whole system. However, in the absence of aggregates, a design that starts as a relatively basic relational graph may evolve into a sprawl, but aggregates contain intrinsic limits that preclude the emergence of sprawls (Sharif et al., 2021). This facilitates the declaration of ownership over goods, the extraction of various services, and the construction of readily comprehendible database queries. As there are no ad hoc transactions or custom locks inside each integration, these rules are aggregated.

On the other side, it has been proposed that web services have a way for dynamically aggregating model results as necessary (Büyükselçuk 2022). These skills are essential for the creation, resolution, and processing of all DSS parameters. Due to the availability of several complex Web services, Yathiraju (2022) states that one of the most well-known aggregations programmed, named Application Service Provider (ASP), which was first "hyped" but eventually failed in the early days of the Internet, is becoming viable. The changes made to data authentication and security, the metering of model component consumption, and the introduction of a per-use payment channel all contributed to this success. As these obstacles are addressed, it is possible that the next generation of DSS will be built by combining the model creation skill of one ASP with the model solution capabilities of another ASP. Nevertheless, the integration of DSS development with other expert systems, including as artificial intelligence, the internet of things, and neural networks, is also a significant area of research for future DSS development.

#### 4.2.5 When a DSS is presented via a web browser, spreadsheet, or immersive graphics, what sacrifices are made? What kinds of user interfaces should the next generation of DSS feature? What must be the major emphasis?

Eisingerich et al., (2019) has found that enhancing user engagement has always relied significantly on the user interface design and it is challenging to design a multi-media interface using synthetic language as the primary focus. Given the multinational and diverse nature of the organizations, the user interface must be designed to suit a broad variety of users and varied decision-making situations (Nasir et al., 2021). Using data that may be derived from recorded history, it is now possible, owing to cutting-edge technology, to design user interfaces that are individually suited to the requirements and tastes of the user. This adaptable and diverse interface will take center stage as the primary attribute feature that developers should priorities.

#### 4.2.6 Does the designed software reflects societal features such as market culture and social norms? Does emergent behavior in a particular field contribute to the forecasting of social trends?

Social connections have been increasingly included into simulation development till recently Friedman and Hendry (2019) as it is encompassing any reciprocal stimulus or reaction between two or more persons. These interactions include the formation of cooperation and rivalry, the ascent of status and positions, the dynamic group behavior, leadership, and normalcy (Antosz et al., 2021). As according to Dieter et al., (2019), there are some fundamental aspects of social interactions that must be included into model creation in every context of application such as the varied forms of social relationships among users, organizational hierarchy, may have an influence on the efficacy of the DSS and thus, need detail study for future development. In other circumstances, the programmed is developed using technical language and regulations, making it challenging for other organizational hierarchies to perform the simulation Little et al., (2019).

Other than that, individual characteristics, including preferences, ideology, beliefs, and perceptions, are the subsequent mitigating elements (Nawari et al., 2019) has concluded that individuals may respond differently to same stimuli or sensory information. This is a product of the undetermined personal preferences that existed before to the acceptance of the scenario. Individuals' preferences also change when they are exposed to a variety of attributes, trends, and levels of the produced software. This emergent behavior therefore altered the forecast made by DSS. A reasonable simulation using an infinite number of components is an intriguing research horizon that will provide researchers with unexplored questions.

## 5.0 CONCLUSION AND FUTURE WORK

This research examined the behavior and theoretical features of the DSS development developed specifically for lean adoption in the industrial sector. Previous study and theory have focused only on the technical components and not the behavioral ones. As the development of emotional intelligence in humankind has progressed, there has been a rise in interest in the study of human behavior in all disciplines. This has implications not only for technical outcomes such as the reduction of lead time, but also for the comprehension of how social outcomes toward the DSS application, such as the readiness, the compatibility with the work culture, and the straightforward operation of the software, will ultimately elevate the function in enhancing the lean productivity. This review's conclusions are constrained by the unique study strategy used. Initially, particular search phrases were utilized to gather the research publications. Second, the collection of components was restricted since various authors used distinct names to describe the same phenomenon. Nevertheless, despite these limitations, this work adds to the existing corpus of thought. In an effort to give a future proposal for the DSS in the lean manufacturing sector, this article proposes that the next research aim to enhance the knowledge and theory development via conceptual debate.

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