How well do decision support systems help decision makers? An examination of adopting lean manufacturing processes

Nur Ain Qistina Muhammad Shafee\textsuperscript{a} | Effendi Mohamad\textsuperscript{b} | Mohamad Soufhwee Abd Rahman\textsuperscript{a} | Muhammad Khairul Hamizan Mohamad Zaidi\textsuperscript{c} | Teruaki Ito\textsuperscript{b} | Oke Oktavianty\textsuperscript{c}

Abstract Choice is crucial for industrial enterprises as their success or failure may depend on it. Consequently, emerging technologies, especially Industry 4.0 (I4.0) are making precision decisions and enabling enriching collaborations with the industry’s computer-assisted decision support systems (DSSs). However, the arrival of Industry 4.0 poses challenges to this emerging application in terms of data variations and interconnectivity. A thorough search across Scopus, Web of Science, and Emerald Science databases yielded 2023 relevant documents. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), the top 250 academic documents were meticulously filtered and analysed in this study. The analysis resulted in the classification of the four main purposes of a DSS as data evaluation, optimisation, scheduling, and selection. The research also investigated the impact of DSSs on the performance of lean manufacturing (LM). Next, this research discussed the controversies with regard to the confidence, prejudice, and discrimination of users, discipline-based DSS application bias, as well as criticisms and suggestions for the future development of DSS, especially in the manufacturing industry. It is believed that, based on its novel findings, this work will pave the way for future research in the same field.

Keywords: decision support system (DSS), DSS development, DSS controversies, manufacturing industry, PRISMA

1. Introduction

Decision, as defined by Psarommatis et al. (2022), is the act of making a choice or reaching a conclusion after considering various options or alternatives. The process involves analysing information, evaluating potential outcomes, and selecting the best course of action based on the available information. There are several types of decisions, including routine decisions, which are made quickly without much thought, and nonroutine decisions, which require conscious analysis. In line with computerisation technology, researchers have focused on creating a system known as a decision support system (DSS) (Posavac et al., 1997) to assist decision-makers in solving specific types of problems. Early development was typically rule-based, using a straightforward mathematical equation for the data analysis to decide. With the advancement of technology in the 1970s and 1980s, DSSs have become more sophisticated, especially with the introduction of advanced modelling techniques with the increasing capacity to handle the data (Forman et al., 2001). This eventually led to the development of complex DSSs to assist decision-makers in a wider range of applications, including finance, healthcare, military, and logistics (Gregory, 2012; Arnott, 2014; Jain, 2021). Meanwhile, starting in the 1990s and 2000s, the rise of the internet and advances in data analytics (DA) steered the development of web-based DSSs to enable decision-makers to access data and analytical tools from anywhere in the world without any time restrictions (Ulfa, 2021).

Today, DSSs continue to evolve with the progression of Industry 4.0 and the introduction of machine learning techniques that allow for more advanced modelling and analyses. Accordingly, this evolution has led to real-time data management for sustainable reversible systems. This architectural technology also represents a decentralised decision concept for data control by compelling predictions at the fastest possible speed. Ito et al. (2021) concluded that this giant leap expedites the decision-making process, thus increasing human productivity.

Surprisingly, little research has been conducted on the development and implementation of DSSs in the manufacturing industry (Mohamad et al., 2020). In addition, little is known about the controversies and drawbacks of DSSs among scholars. As such, this novel work aimed to document the evolution, current trends, and controversies surrounding the application of DSSs, specifically in the manufacturing industry. This research was prompted by the following questions:

a) Which DSS characteristics mediate the correlation between lean manufacturing (LM) and DSS?
b) How DSSs improve LM performance?
c) How does discipline-based DSS application bias affect user confidence in DSSs?

Following this introduction, Section 2 describes the employed methodology. Section 3 describes the evolution of DSSs in the manufacturing industry, while Section 4 examines controversies in terms of ethical concerns and potential bias. Section 5 provides a summary of the entire endeavour. The purpose of this paper was to synthesise the findings into a set of key issues that will assist DSS researchers in developing relevant research agendas, both theoretically and practically.

2. Methodology

In this paper, a literature review on DSS applications was carried out in several stages, beginning with the sorting out of the sources by filtering the focus area of the paper. The selection of the sources was based on the following criteria: (i) the document had to be in journal format, (ii) the discussion must concern the manufacturing industry, (iii) the timeframe must be from 2011 to 2023, according to the development of Industry 4.0, and (iv) the keywords used for browsing were (Decision Support System) and (Lean Manufacturing). The articles on DSSs were selected electronically by examining the keywords and titles in scholarly databases (Scopus, Web of Science, and Emerald Science). This was followed by a manual check that was performed by scanning the table of contents to ensure that the sources were reliable and fulfilled the criteria set for this work. Overall, a total of 2023 articles were identified. It was critical to carefully identify and pick the relevant articles to ensure the credibility and accuracy of the discovery.

<p>| Table 1 Selected Journals Deccriptions from 2011 to 2022. |
|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|</p>
<table>
<thead>
<tr>
<th>Journal</th>
<th>Origin</th>
<th>Ranking</th>
<th>Journal Orientation</th>
<th>Number of DSS Published</th>
<th>Total Number Of Articles Published</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision Sciences (DS)</td>
<td>US</td>
<td>A</td>
<td>Multidiscipline</td>
<td>496</td>
<td>963</td>
<td>51.50</td>
</tr>
<tr>
<td>Decision Support System (DSS)</td>
<td>US</td>
<td>A</td>
<td>General IS</td>
<td>788</td>
<td>897</td>
<td>87.84</td>
</tr>
<tr>
<td>European Journal of Information Systems (EIJS)</td>
<td>Europe</td>
<td>A</td>
<td>General IS</td>
<td>24</td>
<td>432</td>
<td>5.55</td>
</tr>
<tr>
<td>Grouped Decision and Negotiation (GD&amp;N)</td>
<td>US</td>
<td>Other</td>
<td>Specialist IS</td>
<td>123</td>
<td>323</td>
<td>38.08</td>
</tr>
<tr>
<td>Information and Management (I&amp;M)</td>
<td>US</td>
<td>Other</td>
<td>General IS</td>
<td>89</td>
<td>238</td>
<td>37.39</td>
</tr>
<tr>
<td>Information and Organisation (I&amp;O)</td>
<td>Europe</td>
<td>Other</td>
<td>General IS</td>
<td>113</td>
<td>765</td>
<td>14.77</td>
</tr>
<tr>
<td>Information Systems Journal (ISI)</td>
<td>Europe</td>
<td>A</td>
<td>General IS</td>
<td>14</td>
<td>176</td>
<td>7.95</td>
</tr>
<tr>
<td>Information Systems Research (ISR)</td>
<td>US</td>
<td>A</td>
<td>General IS</td>
<td>43</td>
<td>185</td>
<td>23.24</td>
</tr>
<tr>
<td>Journal of Information Technology (JIT)</td>
<td>Europe</td>
<td>Other</td>
<td>General IS</td>
<td>22</td>
<td>667</td>
<td>3.30</td>
</tr>
<tr>
<td>Information of Management Information System (JMIS)</td>
<td>US</td>
<td>A</td>
<td>General IS</td>
<td>67</td>
<td>245</td>
<td>27.34</td>
</tr>
<tr>
<td>Journal of Manufacturing Technology Management Industrial Engineering and Management Systems</td>
<td>UK</td>
<td>A</td>
<td>Multidiscipline</td>
<td>78</td>
<td>329</td>
<td>23.70</td>
</tr>
<tr>
<td>ARPN Journal of Engineering and Applied Sciences Concurrent Engineering Research and Application</td>
<td>Korea</td>
<td>Other</td>
<td>Multidiscipline</td>
<td>87</td>
<td>587</td>
<td>14.82</td>
</tr>
<tr>
<td>Concurrent Engineering Research and Application</td>
<td>Pakistan</td>
<td>Other</td>
<td>Multidiscipline</td>
<td>45</td>
<td>657</td>
<td>6.85</td>
</tr>
<tr>
<td>TOTAL</td>
<td>2023</td>
<td>6709</td>
<td>30.15</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A large number of high-quality journals from Scopus, Web of Science, and Emerald Science were used to provide evidence of the transparency of the knowledge being documented, including editorial boards, indexing status, the peer review process, reputation, and publication policies. The classification began with the location, which was largely determined by the location of the publisher rather than that of the authors. Next, the quality of the journals was categorised as “A” or “Other”. This classification was based on the ranking of the journals according to their publications, where “A” journals were grouped as Q1 and “Other” journals were grouped as Q2, Q3, and Q4. Finally, the journals were sorted into general information systems (IS) and multidisciplinary journals, depending on the orientation of the information provided by them concerning comprehensive knowledge.

Table 1 shows the distribution of these papers by journal as well as the percentage of papers in each journal that were classified as a DSS, as defined by this research. Overall, 15.2% of the papers published between 2012 and 2023 were about the implementation of DSSs. When only the general IS journals in the sample were examined, the proportion of DSS articles was very healthy at 19.1%. Each of these measures indicated that DSSs are an important part of information systems.
Next, all 2023 articles from the previous stage were reviewed and analysed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, as illustrated in Figure 1 above. In this regard, the information gathered from the 230 final documents were discussed in terms of the objectives and benefits, components and key features, recent trends in development, and acceptance of DSSs among users. Here, the discussion was extended to the issues that arose from the analysis of the contents of the articles in terms of case studies, design science, professional relevance, industry funding, and theoretical foundations. In turn, suggestions for future development, including the key features of the development of the basic system as well as collaborations with any other technology such as Industry 4.0, were presented as the final findings of this research.

3. Findings and Discussion

This section provides a comprehensive analysis and interpretation of the results of the study in the context of the existing knowledge in this field. It is an opportunity for researchers to delve more deeply into the implications and significance of their findings, compare them with those of previous studies, and explore possible explanations for the observed outcomes. A DSS is an informational computer system that facilitates decision-making. It may be completely automated, human, or a hybrid of the two. A DSS can improve the efficiency of manufacturing processes by equipping decision-makers with analytical tools and information management capabilities to assist in the resolution of relatively complex, unstructured problems. A DSS also enables decision-makers to communicate and solve problems interactively. The discussions have been divided into three sections to answer the research questions that initiated this entire study.
3.1. Decision support system (DSS) characteristics that mediate its correlation with lean manufacturing (LM)

3.1.1. Components and Key Features of Decision Support Systems (DSSs)

A DSS uses various technologies, including decision analyses, optimisation algorithms, and program scheduling procedures, to create models that aid decision-makers in conceiving alternatives, analysing their impacts, and choosing the most suitable implementation solutions (Landwehr et al., 2022). Every DSS has three fixed components, namely, (i) a data management subsystem (DMS), (ii) a model base management subsystem (MBMS), and (iii) a dialogue generation and management system or what is known as a user interface subsystem, as shown in Fig. 2 below. Other articles also named the components a (i) database, (ii) software system, and (iii) user interface. The database draws on a variety of sources, including internal data related to a company, data generated by applications, and external data collected from third parties (Liesiö et al., 2021). Danilczuk and Gola (2020) discussed the functions of a DSS, which acts as a tool for middle and junior management and offers a novel manufacturing data reporting system built on business intelligence technologies. As an illustration, consider the potential of using data from an ERP system to assist decision-making in small and medium-sized businesses in the areas of purchasing and logistics. Another application is a DSS that is capable of reactively reconfiguring industrial systems to handle disruptions by using an ontology and a multicriteria decision-making technique (Mabkhot et al., 2020). On the other hand, a study by Pérez-Fernández et al. (2022) proved that by using lean techniques and multicriteria analyses to optimise quality expenses in manufacturing, a cutting-edge DSS could be created to efficiently measure and manage intangible costs. For applications in the quality department, this technology expedites and ensures the effectiveness of the decision-making process. Furthermore, this DSS can be used by any manufacturing industry.

![DSS Component](image.png)

**Figure 2 DSS Component.**

The primary aspects of a DSS for the manufacturing industry are the analytical tools and information management capabilities that facilitate the resolution of relatively large, unstructured problems (Gheibi et al., 2022; Rye et al., 2022). A DSS for manufacturing can facilitate decision-making by equipping decision-makers with the resources and knowledge needed to make prudent decisions and improve the performance of the manufacturing industry (Li et al., 2022). One study documented the development of a DSS to configure spare parts supply chains by considering different manufacturing technologies, improving the effectiveness of LM, integrating manufacturing processes in microfactories for electric vehicles, and automating decision-making in the era of zero-defect manufacturing (Fu et al., 2023; Brito et al., 2020; Antomarioni et al., 2021). This DSS provides real-time data and analytics to decision makers to improve supply chain management, expedite decision-making, and optimise production procedures (Anjum et al., 2022) since the primary objectives of a DSS in the manufacturing industry are to improve decision-making procedures, boost productivity, and enhance performance outcomes.

3.1.2 Objectives and Benefits of Decision Support Systems (DSSs)

The function of a DSS is to assist decision-makers in resolving relatively complex, unstructured problems by integrating multiple technologies and analytical instruments (Wang et al., 2022). A DSS employs analytical methods, such as decision analyses, optimisation algorithms, itinerary scheduling routines, and information management capabilities, to assist decision-makers in formulating alternatives, analysing their impacts, and interpreting and selecting the most suitable implementation options (Zarte et al., 2019); one such example is the use of DSSs for waste management (Mohamed et al., 2019). In the manufacturing industry, the goal of a DSS is to increase the efficacy of LM processes by equipping decision makers with analytical tools and information management capabilities to assist in the resolution of relatively large, unstructured problems (Kim et al., 2019). A supplementary clarification involves a DSS proposition that utilises real-time, postprocessed numerical
weather forecasts. This system enables user interaction through a graphical interface to manage program operations, algorithmic processes, and data flow. This ensures the meticulous execution of the final product transportation process (Mazor, 2015). A DSS for economic evaluation in the phosphorus chemical industry is another example of a DSS that facilitates rational decision-making and reduces poor investment (Lewis et al., 2023). Alqahtani et al. (2016) highlighted that DSS processing involves activities that lead to the identification of potential solutions and alternatives that should be considered when addressing unstructured problems. It has been argued that a DSS relates not only to the provision and identification of alternatives but also to the generation of alternatives that would best align with the problem solution. A further example is a DSS for LM that improves the efficiency of manufacturing processes by equipping decision-makers with analytical tools and information management capabilities to assist in the resolution of relatively large, unstructured problems with complex data structures (Bumblaunskas et al., 2017). Hence, Table 2 below shows the traditional DSS category that has been classified into seven subfields (Urban et al., 2022; Teles et al., 2022; and Dubey et al., 2015) based on the generic nature of their operations.

### Table 2 Traditional DSS categories and descriptions (Urban et al., 2022), (Teles et al., 2022), and (Dubey et al., 2015).

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>File-drawer</td>
<td>This type of DSS primarily provides access to data stores/data related items</td>
</tr>
<tr>
<td>Data analysis systems</td>
<td>This type of DSS supports the manipulation of data through the use of specific or generic computerised settings or tools.</td>
</tr>
<tr>
<td>Analysis information systems</td>
<td>This type of DSS provides access to sets of decision-oriented databases and simple small models</td>
</tr>
<tr>
<td>Accounting and financial systems</td>
<td>This type of DSS can perform ‘what if analysis’ and calculate the outcomes of different decision paths.</td>
</tr>
<tr>
<td>Representational models</td>
<td>This type of DSS can also perform ‘what if analysis’ and calculate the outcomes of different decision paths, based on simulated models.</td>
</tr>
<tr>
<td>Optimisation models</td>
<td>This kind of DSS provides solutions through the use of optimisation models which have mathematical solutions</td>
</tr>
<tr>
<td>Suggestions models</td>
<td>This kind of DSS works when the decision to be taken is based on well-structured tasks.</td>
</tr>
</tbody>
</table>

However, the modern narrative of a DSS has changed according to its vast scope of application. Although DSSs and LM are two distinct concepts, they are closely related within the context of their application to improve overall operational efficiency. The role of DSSs in LM is to enhance processes and improve decision-making by aiding organisations in identifying waste, selecting the most appropriate tools, and providing accurate, realistic, and real-time information to enable decision-makers to take the necessary action for any required decision. A DSS can also intersect with the LM philosophy, and they can complement each other in several ways to reduce waste and enhance decision-making in an organisation through real-time data analysis, waste identification, process improvement, root-cause analysis, continuous monitoring and visualisation, and cross-functional collaboration. In a manufacturing setting, DSSs can be used to support and analyse complex decision problems at the strategic and tactical levels as well as improve the efficiency of manufacturing processes by providing decision makers with analytical tools, information, and management capabilities to aid in solving relatively large, unstructured problems through interactive communication and problem solving (Cantini, 2022). In conclusion, as described in Table 3 below, the modern consensus on DSS classification has been divided into five main classes, namely, model-driven, data-driven, communication-driven, document-driven, and knowledge-driven DSSs.

### Table 3 Modern narrative of DSS classification in the LM industry.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model-driven</td>
<td>DSS that uses a quantitative model to derive solutions to issues based on heuristics, optimisation, simulation, etc. It is able to modify the model's parameters and has access to the models. The model is then applied to actual data, or transactional data, from databases in order to determine the answer. The system has the ability to generate various scenarios.</td>
</tr>
<tr>
<td>Data-driven</td>
<td>DSS that provides internal time-series data access. Advanced systems include data warehousing facilities equipped with tools that enable the manipulation of such data. Data-driven DSS includes, for example, executive information systems.</td>
</tr>
<tr>
<td>Communication-driven</td>
<td>DSS that facilitates decision-relevant cooperation and communication through the use of network and communications technologies. Communication technologies are the most crucial element in these kinds of systems.</td>
</tr>
<tr>
<td>Document-driven</td>
<td>DSS that provides document retrieval and analysis through computer processing and storage.</td>
</tr>
<tr>
<td>Knowledge-driven</td>
<td>DSS that gathers and preserves &quot;expertise&quot; for use in making decisions as needed.</td>
</tr>
</tbody>
</table>
Another interesting example of the application of DSSs in the implementation of LM is the emergence of manufacturing resource planning (MRP), such as the configuration of supply chains for spare parts by considering the monitoring and management of a company's stock levels. In this case, the DSS will analyse a variety of criteria, including demand projections, lead times, supplier performance, and cost considerations, to help optimise inventory decisions and to make educated judgements about when to purchase supplies, how much to order, and when to replenish the inventory (Raigar et al., 2020). Another example of the use of a DSS to aid in decision-making in the manufacturing industry concerns the selection of an additive manufacturing (AM) process utilising a new hybrid MCDM technique (Stavropoulos, 2021). A two-stage DSS for the integration of manufacturing processes in microfactories for electric vehicles is another example of a DSS that can aid in decision-making in the manufacturing industry (Richardson et al., 2018). A hybrid DSS for the automation of decision-making in the event of defects in the era of zero-defect manufacturing is another example of a DSS that can assist with decision-making in the manufacturing industry (Kocsi et al., 2020). On the other hand, Watkins et al. (1995) stated that DSSs are being used to strengthen the decision-making process, increase efficiency, and enhance the quality of product outcomes. This study concluded that six main DSS classifications, as shown in Table 4 below, have been specifically utilised in the manufacturing industry for the past five years, namely, (i) statistical models, (ii) sensitivity analysis models, (iii) optimisation analysis models, (iv) backwards analysis, (v) sensitivity models, and (vi) forecasting models.

Table 4 DSS Model for LM Implementation.

<table>
<thead>
<tr>
<th>DSS Model</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistical Models</td>
<td>These models are used to establish relationships between events and factors to that event.</td>
</tr>
<tr>
<td>Sensitivity Analysis Models</td>
<td>These models are used for “what-if” analysis</td>
</tr>
<tr>
<td>Optimisation Analysis Models</td>
<td>These models are used to find the optimum value for a target used in relation to other variables</td>
</tr>
<tr>
<td>Backwards Analysis Sensitivity Models</td>
<td>These models set a target value for a particular variable and then determine the values other variables need to hit to meet the target value</td>
</tr>
<tr>
<td>Forecasting Models</td>
<td>These models are used to analyse business conditions and make plans, including regression models and time-series analysis.</td>
</tr>
</tbody>
</table>

3.2. The effect of decision support systems (DSS) on lean manufacturing (LM) performance

3.2.1. Recent Decision Support System (DSS) Trends

Consequently, the following discussion will touch on recent advancements in DSSs that focus on the incorporation of diverse technologies and the facilitation of LM performance via the selection of solutions for relatively large, unstructured problems. The current trend in DSSs is the development of more agile and data-driven systems, which means using the categorised data provided to illuminate the decisions made (Eom et al., 2022). The quantity and scope of the information provided by information technology have become overwhelming, resulting in cognitive excess, confusion, and an inability to function effectively (Guo, 2020). DSSs are being developed to expedite data analysis and the selection of a viable course of action. Another trend in the creation and administration of DSSs is the use of data mining (Arnott, 2019). The creation of DSSs based on data extraction is the most pressing trend in the development of decision-making systems (Parra et al., 2019). In addition, the focus of DSS research has shifted from individual DSSs to group DSSs, model management, and design and implementation (Liao et al., 2021). The prevalence of internet-based DSSs has been on the rise since the late 1990s (Taylor et al., 2023). Modern systems of web recommendations are being developed to provide users with customised recommendations based on their preferences and behavior.

The selected papers are representative of current research activities in the field of DSSs, with a focus on topics such as decision analysis, integrated solutions for decision support and knowledge management in distributed environments, the evaluation and analysis of DSSs through social networks and e-learning, and their application in real-world settings (Ang et al., 2023). Recent advancements in DSSs have centred on enhancing decision-making through the incorporation of diverse technologies and analytical tools, as well as the evaluation and analysis of DSSs via social networks. A different article incorporated the expanded and revised versions of selected papers presented at two workshops organised by the Euro Working Group on DSSs, concentrating on topics such as decision analysis for enterprise systems and nonhierarchical networks, utilising the statistical modelling technique to find the relationship between events and factors related to that event (Mendes et al., 2021). Another paper (Deitermann et al., 2022) discussed the construction of a decision-making support system for fast-growing and high-yield forests based on grid technology, employing system engineering approaches and combining the technologies of XML, web services and data grids to produce forest management schemes with real-time, veracity, quantity, and optimisation, providing an example for sensitivity analysis models. Recent trends in DSSs include the incorporation of various technologies, such as grid technology and Web-GIS technology, to provide more efficient and effective support for decision-making in a variety of industries.
Consequently, there is a dearth of empirical research describing the effects of DSSs on manufacturing productivity, with the optimisation analysis model appearing to be the most famous DSS model in use. Moreover, a more reliable, robust, and systematic decision support tool has been proposed for the sequential implementation of lean adoption solutions in SMEs that lack the resources to simultaneously address all solutions. Numerous examples of DSSs have been developed for the LM sector. One such tool is the Lean Tools Selector, which is aimed at assisting organisations in identifying waste and selecting the most suitable tools or lean practices for implementation (Jituri et al., 2021). Another benefit of forecasting models is that they assist organisations in planning and structuring their actions at development while ensuring that they support the entire organisation and not just a few individuals. The next example from the study (Ito et al., 2020) is the Internet of Things (IoT) and the simulation approach for a DSS in LM, which intersects the Andon system and where simulation is conducted through IoT concepts to provide improved information flow for decision-making. DSSs have been implemented in LM for the assembly of automotive components and can be readily adopted in digital factories to support both planned and operational activities via the use of sensors for real-time data collection (Lu et al., 2020). A third example is a DSS that is aimed at defining, evaluating, and directing lean assessment and implementation on the shop floor (Aramja et al., 2020). The system provides a method for assessing the current condition of an organisation, identifying areas for improvement, and developing a plan for the implementation of lean practices. Overall, these examples illustrate the significance of DSSs in the LM industry, as they provide decision-makers with the necessary tools and information to make informed decisions and enhance manufacturing industry outcomes.

In conjunction with that, another literary gem revealed a procedure for constructing a DSS backwards analysis sensitivity model for effective interventions and maintenance in manufacturing using the example of a predictive mode from the electronics industry (Shojaeinasab et al., 2022), where this model is being used in the steel industry for the development and testing of production execution systems (Lee at al., 2020). In addition, smart manufacturing technologies have also utilised this model to provide decision-making support to manufacturers via enhanced monitoring, analysis, modelling, and simulation to generate increasingly better intelligence about manufacturing systems (Connell et al., 1992; Kayacik et al., 2022). However, obstacles and challenges have hindered the adoption of smart manufacturing technologies, and efforts are required to promote a common understanding among the manufacturing community that can enable standardisation efforts and the innovation required to continue the adoption and use of smart manufacturing technologies (Noriega, 2020; Jakku et al., 2010). In addition, intelligent maintenance systems (IMSs) also use backwards analysis sensitivity models to provide decision support tools to optimise maintenance operations and intelligent prognostic and health manufacturing tools that are essential for identifying effective, dependable, and cost-effective maintenance strategies to ensure consistent production with minimal unplanned downtime (Fiarni et al., 2019). Overall, the literature strongly suggests that DSSs should be utilised in the manufacturing industry to assist decision-makers in various aspects, including effective interventions. It can be concluded from this discussion that the impact of DSSs on the performance of LM can be determined by comprehending three important aspects: waste identification and elimination, accurate and up-to-date information, and the integration of lean and agile production, as described in Figure 3 below.

**Figure 3** DSS characteristics that mediate implementation within the LM industry.

- **Waste Identification & Elimination**
  - DSS can assist organisations in identifying waste and selecting the best tools or lean practices to implement. This can assist organisations in reducing waste and boosting productivity.

- **Accurate & Up-To-Date Information**
  - DSS can provide accurate, realistic, and up-to-date information to decision-makers, allowing them to take the necessary actions to achieve effective production and material planning and control. This can assist organisations in making more informed decisions and improving their processes.

- **The Integration of Lean & Agile**
  - DSS can incorporate lean and agile production concepts to provide management with accurate, realistic, and up-to-date information, allowing decision-makers to take the necessary action to achieve effective production and material planning and control. This can assist organisations in becoming more adaptable and responsive to changing customer needs.
This section further discusses the strengths and weaknesses of DSSs in the literature. The ability of a DSS to provide decision-makers with access to vast quantities of data and information to assist them in making more informed decisions (Okunlaya et al., 2022) has been one of its greatest strengths since its inception. A DSS can also assist decision-makers in analysing complex problems and identifying possible solutions (Dennehy et al., 2019). With modernisation, DSSs have become interactive and user friendly, which can increase their adoption and utilisation by decision-makers (Li et al., 2022). However, DSSs also have vulnerabilities. One of their weaknesses is that they may rely on incomplete or inaccurate data, which can result in biased or incorrect decisions (Kühl et al., 2022). DSSs may also be limited by the quality of the data analysis and recommendation algorithms (Rao et al., 2022). In addition, DSSs may be constrained by the knowledge and experience of their users, as well as their propensity to adopt new technologies (Hornsby et al., 2022). Overall, the strengths and limitations of DSSs indicate that they can be valuable decision-making tools, but their efficacy is contingent on the data and algorithms employed, as well as the expertise and experience of the decision-makers who employ them. The limitations of DSSs include their potential to incorporate biases, errors, and inaccuracies into decision-making processes, as well as their potential to result in an overreliance on technology and less reliance on human judgment in decision-making (Airaldi et al., 2021). In addition, the development and implementation of a DSS may require substantial resources, including time, money, and specialised knowledge, and may encounter obstacles related to data quality, system integration, and user acceptance. In addition, a DSS may not be effective in solving all types of problems, especially those that are highly structured or require subjective judgment (Karkošková et al., 2023).

In the context of intelligent manufacturing, the limitations of DSSs may include their inability to manage complex and dynamic manufacturing processes, lack of flexibility and adaptability, and inability to incorporate human expertise and knowledge into decision-making processes (Hammond et al., 2023). In general, the limitations of DSSs should be carefully considered when designing and implementing these systems, and guidelines and frameworks should be developed to ensure that DSSs are used in a manner that is consistent with ethical standards and that promotes transparency, accountability, and fairness. In addition, new generations of DSSs should be developed to address the limitations of existing systems and to meet the changing requirements of decision-makers across industries.

The literature suggests numerous methods for enhancing DSSs to surmount their limitations. One method for enhancing data integrity, system integration, and user acceptance is to involve stakeholders in the development and implementation of a DSS (Fradda et al., 2022). Another strategy is to establish a framework for evaluating the performance objectives and capabilities of DSSs in their ongoing development and use from the perspective of key stakeholders (Kumar et al., 2022). In addition, recent developments associated with DSSs in the agriculture sector have centred on the integration of various technologies and analytical methods, such as decision analyses, optimisation algorithms, and scheduling routines, to assist decision-makers in formulating alternatives, analysing their impacts, and selecting the most appropriate implementation options (Tian et al., 2022). A new generation of DSSs is required to surmount the limitations of decision support for intelligent manufacturing (Sternberg et al., 2023). Furthermore, the correct use of management decision-making tools can assist businesses in achieving their short- and long-term objectives, making well-balanced decisions that primarily benefit the business or organisation, and resolving problems that arise from their activities (Pantano et al., 2022). To enhance DSSs and overcome their limitations, it is crucial to involve stakeholders in their development and implementation, develop frameworks to assess their performance objectives and capabilities, integrate diverse technologies and analytical methods, and use management decision-making tools to achieve short- and long-term objectives. To conclude, Figure 4 below lists all the weaknesses of the DSSs that were discussed.

<table>
<thead>
<tr>
<th>DSS Weakness</th>
<th>Highly Structured for Certain Subjective Judgment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expensive for certain sectors</td>
</tr>
<tr>
<td></td>
<td>Limited by Certain Specific Expertise</td>
</tr>
<tr>
<td></td>
<td>Limited to the Algorithms used</td>
</tr>
<tr>
<td></td>
<td>Incomplete or Inaccurate Data Collected</td>
</tr>
<tr>
<td></td>
<td>Lack of Human Intelligence Corporation</td>
</tr>
<tr>
<td></td>
<td>Time Consuming for the Adoption</td>
</tr>
<tr>
<td></td>
<td>Lack of transparency</td>
</tr>
<tr>
<td></td>
<td>Prone to be Biased</td>
</tr>
</tbody>
</table>

Figure 4 DSS Weakness.

This deception has been discussed from a censorious and caustic perspective of controversies, ethical concerns, and possible manufacturing-based biases. It is evident that the primary development of DSSs in the manufacturing industry is to
support strategic, tactical, and deliberate production to enable decision-makers to conduct what-if analyses in real time and make sound decisions regarding future consequences in the shortest possible time (Kirchhoff et al., 2022). When technologies such as DSSs are used in multiple industries or when organisations attempt to transfer solutions across domains, application discipline bias becomes especially important. To address this bias, when designing and implementing technological solutions, it is critical to consider the unique needs and characteristics of each discipline. Customisation, flexibility, and interdisciplinary collaboration can all help to reduce bias and make systems more versatile and adaptable to a wide range of applications. The term ‘application discipline bias’ refers to the influence of a specific field or industry on the design, development, and application of technologies, tools, or systems. This reflects the idea that systems or solutions may be designed with a bias towards a particular discipline or industry, which can affect their relevance or effectiveness when applied in other domains. Application bias is particularly relevant when technologies such as DSSs are used in diverse industries or when organisations attempt to transfer solutions across different domains. The details are explained in Figure 5 below as follows: specific industry or field focus, domain-specific language and concepts, modelling assumptions, data quality and security, customisation and adaptability, user training and familiarity, and feedback and validation.

### Figure 5 DSS application discipline.

For instance, in this study, a DSS was developed to support strategic production allocation to enable managers to determine the optimal production line for producing the highest volume of raw sources at the quickest rate to affect the economic evaluation of basic materials, especially in the food manufacturing industry, which is advantageous for rational decision-making and the reduction of poor investments in the research and development sector (Zhang et al., 2021). Using system engineering approaches, a decision-making support system was developed for the cultivation and management of a rapidly growing and high-yield wood manufacturing industry to influence the decision-making process for various tree species, terrains, and site conditions and indirectly affect the climate and geometric growth (Gergio et al., 2021). DSSs may be a relatively new and developing field in the manufacturing industry, and as their technology and applications continue to evolve, controversies may arise. Overall, additional research is required to ascertain the potential controversies surrounding DSSs in the manufacturing sector and their impact on decision-making and outcomes. However, it has also been reported that the implementation of DSSs has given rise to controversies regarding their application. First, DSSs may become excessively dependent on technology, which could lead to a disregard for human knowledge and experience. This can result in faulty decision-making or a lack of creativity when solving problems (Danilczuk et al., 2020). In addition to data quality, DSSs require vast quantities of data to function effectively, and the quality of these data can vary greatly (Mabkot et al., 2020). If decision-makers rely excessively on DSSs without verifying the veracity of the data, incorrect or misguided decisions can result (Pérez-Fernández et al., 2022). In achieving success, the disagreement stems from a lack of transparency due to the inscrutable algorithms employed, meaning that it is not always possible to reach a particular decision without examining the equation parameters in minute detail (Urban & Tochwin, 2022). Finally, the cost of implementing and maintaining such systems can be high since they require a modern structure and can only be operated by individuals with specialised knowledge (Teles et al., 2022). This will increase the burden on entrepreneurs, especially in the SME sector.

#### 3.2.2. Ethical Concerns for Discipline-based Decision Support System (DSS) Application Bias

According to Dubey and Singh (2015), the use of DSSs in the manufacturing industry may raise ethical concerns if they do not promote standards, respect the privacy of employees, or permit worker autonomy. To address these issues, Smith-Renner (2020) suggested that DSSs should be designed to promote standards, be transparent, and be accountable. In addition, DSSs should be designed to respect the privacy of workers and to permit worker autonomy, such as by allowing workers to opt out of certain decision-making processes or to provide input during the decision-making process. Designing a DSS to address ethical concerns requires careful consideration of the potential ethical implications of the DSS and the development of ethical frameworks and guidelines to ensure that the DSS is designed and utilised in a manner that promotes ethical values and principles. In addition, there are fears that malfunctions or the improper use of medical DSSs (MDSSs) could endanger the health of patients (Heider et al., 2022; Alkaraiji, 2017). Supplementary ethical considerations of artificial intelligence in clinical decision support include patient safety, effectiveness, transparency, accountability, and sustainability (Purushothaman et al., 2021). These reservations may also apply to the use of DSSs in the manufacturing sector, where the potential for damage to employees or the environment may be a concern. Potential ethical concerns associated with the use
of DSSs in the manufacturing sector may include issues of trust, transparency, accountability, potential damage, and the effect on employees and the environment. To address these concerns, DSSs should be devised and utilised in a manner that promotes ethical values and principles, and guidelines and frameworks should be developed to ensure that DSSs are utilised according to ethical standards. The literature on DSSs in general suggests that DSSs may be susceptible to biases due to incomplete or inaccurate data, defective algorithms, and human decision-making biases (Adensame et al., 2021). Furthermore, the use of DSSs may result in an overreliance on technology and a reduction in human judgement and decision-making, which may result in decision-making errors or biases (Richardson et al., 2021). Additionally, the ethical considerations of artificial intelligence in decision support include bias, impartiality, and equity concerns (Pagano et al., 2022). These concerns are where the biases in decision-making may have implications for workers, the environment, and the overall performance of the manufacturing process. On the whole, to address potential biases in DSSs in the manufacturing industry, it is important to ensure that DSSs are designed and used in ways that promote transparency, accountability, and fairness and that guidelines and frameworks are developed to ensure that they are used in ways that are consistent with ethical standards. According to Emerald (2020), Guccie (2021), and Sophia (2023), ethical concerns within the context of LM implementation can be discussed in terms of several aspects, as shown in Table 5 below:

<table>
<thead>
<tr>
<th>Application-discipline bias</th>
<th>Description</th>
<th>Author</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transparency and Accountability</td>
<td>Access to private and sensitive data, including employee records, production metrics, and intellectual property, is frequently necessary for DSS. If there are privacy or data security breaches that result in unauthorised access to or misuse of this information, ethical questions might be raised. To safeguard sensitive data, strong data security measures must be put in place.</td>
<td>Smith-Renner et al., (2020); Heider et al. (2022); Alkraiji (2017); Purushothaman et al., (2021); Adensamer et al., (2021); Richardson &amp; Gilbert (2021); Pagano et al. (2022); Neal et al. (2022); Gauthier et al. (2022); Akter et al. (2021)</td>
</tr>
<tr>
<td>Bias and Fairness</td>
<td>DSS may treat people or groups unfairly as a result of biases inherited from the data they are trained on. If DSS reinforce or magnify biases based on gender, race, or other protected characteristics, ethical questions might be raised. It is recommended that organisations put strategies in place to detect and reduce bias in DSS algorithms.</td>
<td>Richardson &amp; Gilbert (2021); Pagano et al. (2022); Neal et al. (2022); Gauthier et al. (2022); Akter et al. (2021)</td>
</tr>
<tr>
<td>Accountability for Errors</td>
<td>DSS is not perfect, and its suggestions are not always accurate. These mistakes can have serious repercussions in lean manufacturing, such as resource misallocation and production delays. While assessing who is accountable for these mistakes and their consequences, ethical considerations are relevant. It is essential to establish distinct lines of accountability and duty.</td>
<td>Alfaawaer &amp; Halimi (2022); Rahman et al. (2020); Unver et al. (2020); Ito et al. (2020)</td>
</tr>
<tr>
<td>Job Displacement</td>
<td>DSS can cause job displacement and worker disruptions. To limit the negative impact of technology adoption, ethical issues include how organisations handle workforce changes, reskilling, and assistance for impacted personnel.</td>
<td>Guo et al. (2020); Nye (2020); Hyman et al. (2021); Nedelkoska et al. (2022); Cortes et al. (2020); Harries et al. (2020); Schmillen (2020); Kultzig et al. (2021); Chetsa (2021); Benson et al. (2020); Alasiri &amp; Salameh (2020); Talari et al. (2021); Bowen &amp; Hinze (2022); Gans et al. (2022); Vidgen et al. (2020); Francis &amp; Thomas (2020); Tiwari et al. (2020); Abualfaraa et al. (2020); Awan et al. (2022); Covelli et al. (2021); Zhang et al. (2020); Yoon, Y., &amp; Sengupta, S. (2022); Afzali et al. (2022); Collie et al. (2021); Pettingell et al. (2022)</td>
</tr>
<tr>
<td>Data Ownership and Control</td>
<td>Data used in DSS may be created by staff members and gathered by the company. Concerns about ownership, control, and the rights of the people whose data is utilised might give rise to ethical issues. Establishing explicit guidelines and procedures for data ownership and usage is important for organisations.</td>
<td>Afzali et al. (2022); Collie et al. (2021); Pettingell et al. (2022)</td>
</tr>
<tr>
<td>Environmental Impact</td>
<td>Sustainable environmental practices raise ethical questions in lean manufacturing. To adhere to moral principles of sustainability, DSS should consider how manufacturing decisions affect the environment, including resource use and waste production.</td>
<td>Afzali et al. (2022); Collie et al. (2021); Pettingell et al. (2022)</td>
</tr>
<tr>
<td>Social Responsibility</td>
<td>The goals of lean manufacturing may require decision support systems to compromise on a number of moral principles. The following are a few instances of moral principles that could be violated: Social justice: The DSS may put cost-cutting tactics before of treating workers fairly, which may include lowering pay or benefits or firing employees without providing them with enough assistance or compensation.</td>
<td>Afzali et al. (2022); Collie et al. (2021); Pettingell et al. (2022)</td>
</tr>
</tbody>
</table>
3.2.3. Approaches for Overcoming Discipline-based Application Bias

It is essential to address bias in the DSSs used in the LM industry to ensure fair, accurate, and reliable decision-making. By implementing these strategies, organisations can develop DSSs that are more resistant to bias and that promote fair and equitable decision-making in the LM environment. This, in turn, can lead to improved operational efficiency and reduce the risks associated with bias-related issues. Several strategies can be employed during the development of DSSs to counter bias, as follows:

- **Data Preprocessing and Cleaning:**
  
The data used to train and operate the DSS were carefully preprocessed and cleaned to remove any existing biases. The identification and correction of data inaccuracies and inconsistencies may contribute to bias (Shimron et al. 2021, Mohamed & Kamel, 2020).

- **Diverse and Representative Data:**
  
The training data used to develop the DSS are diverse and representative of the LM environment, including different production lines, processes, and employee demographics. Data from multiple sources can be incorporated to mitigate the risk of data bias (Marcelino et al. 2023, Pozzi et al., 2021, Oukhay, 2020).

- **Algorithm Selection:**
  
  Machine learning algorithms and techniques that are known for their fairness and ability to mitigate bias are selected. For example, some algorithms are designed to reduce disparate impacts and promote fairness in predictions. Interpretable algorithms that provide transparency in the decision-making process should be considered (Tan & Staats, 2020; Kaptchuk et al., 2021).

- **Bias Detection and Mitigation:**
  
  Bias detection tools can be used to identify potential biases in the DSS during the development and deployment phases. Techniques such as reweighting, resampling, and reranking can be applied to mitigate bias and ensure that the DSS provides equitable outcomes.

- **Ethical Guidelines and Policies**
  
  Clear ethical guidelines and policies for the development and use of DSSs in the LM environment should be established. These guidelines outline ethical principles, data privacy rules, and procedures for addressing bias and unfair treatment (Werz et al. 2020; Andreiana et al., 2022).

- **Interdisciplinary Collaboration:**
  
  Interdisciplinary teams should be involved in the development of DSSs. Collaboration among data scientists, domain experts, ethicists, and other stakeholders can help identify and address bias more effectively. Employees and end-users who understand the nuances and potential sources of bias in the manufacturing context seek input (Apiola & Sutinen, 2020; Orphanou et al., 2021; Zhu et al., 2020; Orphanou et al., 2021).

- **Regular Auditing and Monitoring:**
  
  Regular auditing and monitoring processes are implemented to assess the performance of the DSS and detect any emerging bias. The DSS was continuously refined and updated to address new sources of bias (Arifin, 2021; Calles, 2020; Qiu et al., 2020).

- **Transparency and Explainability:**
  
  The DSS is designed to be transparent and explainable. Users should be able to understand how the system arrives at its recommendations. This study provides clear explanations for the factors and data that influence the decisions of the DSS (Warner and Sloan, 2021; Reich et al., 2020).

- **User Feedback and Reporting Mechanisms**
  
  To establish channels for users to report concerns related to bias and unfair treatment. Encourage feedback and actively address issues as they arise. The DSS implements mechanisms for users to challenge or appeal decisions (McCoy & Rosenbaum, 2019; Balayn et al., 2021; Gillingham, 2019).

Regular training in diverse ways:
Both employees and users should be educated on the ethical utilisation of the DSS and the possible origins of bias. Raise awareness regarding the significance of impartial decision-making within the manufacturing setting. The importance of cultivating diversity within development teams should be emphasised, as diverse teams offer varied perspectives, thereby minimising the chance of unintentional biases in the system. Developers from diverse backgrounds can collaboratively recognise and rectify potential biases in algorithms that guide decision-making (McCoy & Rosenbaum 2019; Paradowski et al., 2021; Goldberg et al., 2020; Lai et al., 2020).

4. Final considerations and Future Works

In summary, this paper revealed the evolution of DSSs and trends over the last five years (from 2019 to 2023). The discussion began with the five major components of a DSS: (i) the data management subsystem (DMS), (ii) the model base management subsystem (MBSM), and (iii) the dialogue generation and management system, often known as the user interface subsystem. Other articles have described the components as (i) the DSS database, (ii) the DSS software system, and (iii) the DSS user interface. All the previously selected publications were subsequently reviewed and analysed. In this regard, the information acquired was discussed in terms of the aims and benefits of DSSs, their components and major features, recent development trends, and user acceptance. Then, the discussion was extended to the strengths of the available DSSs as well as the evidence in real cases and their weaknesses, such as the time required for adaptation, limited algorithms, and decisions that are prone to bias. The controversies concerning DSSs were addressed, as well as ethical concerns and potential bias of the application.

A comprehensive investigation should be undertaken in the future to show the financial, mathematical, and artificial intelligence advancements that have been made, such as fuzzy logic, artificial neural networks (ANNs), genetic algorithms (GAs), and expert systems (ESs). Furthermore, another recommendation for the future is to focus on specific types of manufacturing applications and explore their impact at the social, economic, and national levels.

Acknowledgment

This research was supported by the Ministry of Higher Education (MOHE) through a fundamental research grant (FRGS/1/2020/TKO/UTEM/02/42). The authors fully acknowledge the Ministry of Higher Education (MOHE) and Universiti Teknikal Malaysia Melaka for their approval, which made this important research viable and effective.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare that there are no conflicts of interest.

Funding

Malaysian Government via grant FRGS/1/2020/TKO/UTEM/02/42.

References


https://www.malque.pub/ojs/index.php/mr


Research, 293(3), 811-825.
Mazur, A. (2015). Project riot—“ring of threats” as an example of a decision support system (dss), concept and realization. meteorology hydrology and water management. Research and Operational Applications, 3.
Noriega, M. (2020). The application of artificial intelligence in police interrogations: an analysis addressing the proposed effect ai has on racial and gender bias, cooperation, and false confessions. Futures, 117, 102510.
Nye, H. (2020). Technological displacement and the duty to increase living standards: from left to right. The International Review Of Information Ethics.


Yoon, Y., & Sengupta, S. (2022). Can cutting pay be an alternative to cutting people when maintaining work attitudes is a concern? it can be if employees trust you. *Journal of General Management*.


