

## OPERATIONAL DECISION SUPPORT IN MANUFACTURING AND TECHNOLOGICAL INFORMATION PROCESSING: A SYSTEMATIC LITERATURE REVIEW

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### Abstract:

The article is based on a systematic literature review on operational decision support in production and technological information processing. The content analysis aimed to examine how modern information processing systems are integrated into decision-making models in the context of production operations. The literature review follows the PRISMA method, designed to ensure transparent reporting of systematic reviews and meta-analyses. The article covers the following stages: literature search, thematic selection, and quantitative and qualitative analysis of the collected literature. Based on the bibliometric analysis, the literature can be divided into three interrelated thematic areas. The first thematic area concerns operational decision support in production planning, scheduling, capacity allocation, and production control. The second thematic area refers to technological information processing, including the representation of process knowledge through CAD model integration and the interpretation of technical documentation. The third thematic area focuses on tools that have gained increasing importance in recent years in the broadly understood industrial sector: machine learning, digital twins, and Industry 4.0 infrastructure. The literature analysis indicates that a major research gap lies not in the absence of individual decision-support methods, but in the limited integration of operational and technological information within coherent models supporting decision-making under real manufacturing conditions.

**Key words:** decision support systems, technological information processing, manufacturing, engineering drawings, CAD extraction

### INTRODUCTION

Production enterprises operate in an environment in which decision quality depends less on the existence of data alone and more on the ability to transform dispersed technical, process and operational information into usable managerial knowledge. This observation is not new, but its practical consequences are sharper today than in earlier generations of manufacturing systems. Contemporary plants increasingly rely on mixed information ecosystems: ERP and MES platforms, CAD repositories, engineering drawings, bills of materials, and process routing sheets. In theory, these resources should support planning, scheduling, capacity allocation, material preparation, and process selection. In practice, they often remain fragmented, partially structured, and poorly connected to real operational decisions. The result is not merely informational inefficiency. It is delayed decision-making, repeated manual work, inconsistent technological assumptions, and avoidable risk in production execution.

For this reason, the proposed review is built around two domains that are usually discussed separately even though they increasingly depend on one another. The first domain is production operational decision support. This stream covers decision support systems for planning and scheduling, dynamic pro-

duction control and process selection. The second domain is technological information processing. This stream includes the:

- acquisition,
- representation,
- interpretation,
- integration,
- reuse of technological knowledge.

The separation between these thematic areas is one of the main analytical problems in the literature. Many studies optimise a decision process without addressing the upstream quality of technological information. Conversely, many studies address information extraction or representation without following the information into downstream production decisions.

The review therefore adopts an integrative question: *how modern information processing systems are integrated into decision-making models in the context of production operations?*

From a theoretical point of view, it allows the discussion to move beyond isolated tools and toward an information-to-decision architecture. From a practical point of view, it helps explain why many digitalisation projects improve local visibility but fail to produce reliable operational decisions at scale. In enterprises that still depend heavily on 2D documentation, manual interpretation of drawings, and heterogeneous information sources, this issue is especially important. The research topic is relevant for four reasons.

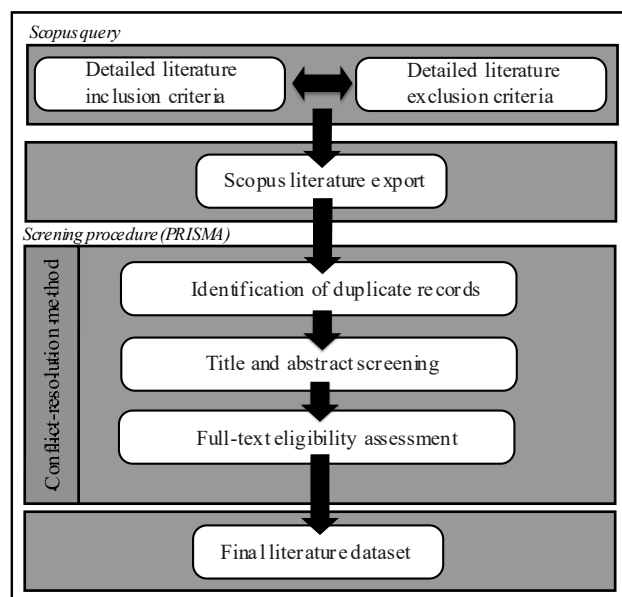
- 1) Recent literature on production decision support has shifted toward hybrid approaches that combine simulation, data mining, machine learning, and interactive analytics.
- 2) Research on technological information processing has accelerated, particularly in product lifecycle management, knowledge representation, and AI-based extraction from technical drawings.
- 3) Industry 4.0 infrastructures are making it easier to connect real-time operational data with engineering and lifecycle information, but methodological fragmentation remains strong.
- 4) Review studies now exist in adjacent areas such as smart manufacturing scheduling, big data analytics in manufacturing, PLM-IoT integration, and process knowledge representation.

Despite the growing number of studies in both domains, there is still a lack of integrated frameworks that connect technical information extraction with operational decision-making models in real manufacturing environments. Most existing approaches focus either on information processing or decision support, but rarely address their full integration. This gap constitutes the main research motivation of the present study.

The objective of this article is therefore twofold. The first objective is to produce a systematic literature review that maps the main conceptual streams, methods, applications, and research gaps. The second objective is to propose a bibliometric layer that quantifies how the field is structured, which themes dominate it, which authors and journals are influential, and which terms co-occur most strongly.

## METHODOLOGY

The research methodology adopted in this study is based on a structured approach to the identification, selection and analysis of scientific literature. The scientific literature concerns the integration of technological information with operational decision support in production environments. The adopted procedure was designed to ensure transparency in the literature selection process, thematic consistency and the possibility of identifying current research directions. The methodological framework is based on the following assumptions: *detailed inclusion/exclusion criteria*, and *screening procedure (PRISMA)* – Figure 1.



**Fig. 1 Literature search strategy-method**

**Alt text:** Flowchart of the literature selection process, including Scopus export, duplicate removal, screening, eligibility assessment, and final dataset.

### Literature search strategy-method

The bibliographic search was conducted in the Scopus database on 29 April 2026. Scopus is one of the most frequently applied sources in bibliometric studies and systematic literature reviews. The choice of this database resulted from its broad coverage of peer-reviewed scientific publications, including the fields of engineering management. The use of Scopus as the primary source of literature retrieval was intended to ensure a sufficiently broad, yet academically reliable, body of publications relevant to the research problem.

The content of bibliographic databases is dynamic and the number of indexed records may change over time due to the addition of new articles, corrections of metadata, and early-access indexing. The reported search date (29 April 2026) defines the temporal boundary of the dataset used in this systematic literature review. The publication time span was limited to the years 2019-2026. This period was selected deliberately in order to focus the analysis on recent scientific contributions reflecting current developments in decision support systems, digitalization of manufacturing processes, and methods of technological information processing. Restricting the analysis to the most recent years made it possible to capture contemporary research trends, including artificial intelligence, automation of information processing, and the integration of technical and production data in digital environments. At the same time, the adopted time horizon remains sufficiently broad to identify dominant research streams, frequently addressed problems and existing research gaps.

The Scopus database was searched using the following query:

TITLE-ABS-KEY ("technical information" OR "engineering information" OR "technical data" OR "engineering data" OR "product data" OR "process data")

AND

("decision support" OR "decision support system" OR DSS ) AND (manufacturing OR production)) AND  
PUBYEAR > 2018 AND PUBYEAR < 2027

The selection of the keywords was directly related to the thematic scope of the study.

The term "decision support system" refers to solutions supporting decision-making processes in the operational activities of manufacturing enterprises. "technical information" covers issues related to the interpretation and use of technological information in production preparation and execution. The search string combined three thematic blocks connected by the Boolean operator AND.

The first block included terms related to the informational dimension of the research problem, namely: “technical information”, “engineering information”, “technical data”, “engineering data”, “product data”, and “process data”. These expressions were intended to capture studies addressing different forms of technical and technological information used in industrial and manufacturing contexts. The second block focused on decision-support-related terminology and consisted of the following terms: “decision support”, “decision support system”, and DSS. This part of the query was designed to retrieve publications referring to both general decision support approaches and formalized decision support systems. The third block defined the application context of the review by including the terms manufacturing and production. This restriction was introduced to ensure that the results were limited to studies situated in industrial and production environments rather than in unrelated sectors.

### **Detailed literature inclusion criteria**

Such a search formula made it possible to identify publications located at the intersection of operational management, information technologies and production engineering. The query was not modified after the screening process had started. This was done to avoid selective adjustment of the search strategy after observing the results. All records retrieved from Scopus on the search date were exported and archived as the raw bibliographic dataset. The exported file constituted the starting point for both the systematic screening procedure and the bibliometric analysis.

No additional records were added manually after the formal Scopus export stage.

The inclusion criteria were defined before the screening stage in order to ensure consistency in the selection of publications. Studies were included if they met all of the following conditions:

- they were published between 2019 and 2026,
- were written in English,
- were indexed in Scopus,
- focused on at least one of the following thematic areas: manufacturing, production engineering, industrial operations, process planning, technological information processing, decision support systems, decision models, or data-driven decision-making in production contexts.

Furthermore, only peer-reviewed scientific publications were considered eligible. The review included journal articles, review articles and conference papers. Inclusion was limited to studies in which the extracted or processed information was explicitly connected with operational decision-making in manufacturing enterprises. The review included studies addressing engineering drawing interpretation, feature extraction, process planning, manufacturing method classification, lead-time prediction and production performance assessment.

### **Detailed literature exclusion criteria**

The exclusion criteria were applied to remove records that were outside the conceptual and methodological scope of the review. Publications were excluded if:

- they did not concern manufacturing, production engineering, industrial operations,
- they did not concern technological information processing in a production-related context.

Records were also excluded when decision-making was discussed only in a broad managerial, economic or policy sense without a connection to operational manufacturing processes.

Editorial notes, and non-scientific commentaries and records without sufficient bibliographic or methodological information were excluded.

Further exclusions were made for duplicate records, records with incomplete metadata, non-English publications, publications outside the 2020–2026 period, and documents for which the abstract and title did not provide enough evidence of relevance.

Full-text exclusion was applied when the title and abstract appeared relevant, but the full paper showed that the study did not actually address manufacturing decision support or technological information processing.

### SCREENING PROCEDURE (PRISMA)

In this study, the PRISMA statement was adopted in the literature screening process, ensuring a structured and transparent approach to systematic reviews and meta-analyses. This method increases the reliability and reproducibility of the review process. The PRISMA framework provides a systematic structure for: *literature identification*, *literature selection*, and *assessment of the literature's relevance to the studied thematic scope*.

### Scopus literature export

The bibliographic records were exported from Scopus using the CSV format. The export included all fields necessary for bibliographic verification, systematic screening and bibliometric analysis. The exported metadata included:

- authors,
- title,
- year of publication,
- source title, volume,
- issue,
- pages or article number,
- DOI,
- abstract,
- author keywords,
- index keywords,
- affiliations,
- cited references,
- citation information.

For the systematic review, the most important fields were: title, abstract, keywords, DOI, source title and year of publication. These fields were used during screening, eligibility assessment and verification of bibliographic consistency.

The original Scopus export was preserved as an unaltered source dataset. Data preprocessing and cleaning were carried out exclusively on a separate working copy, allowing all modifications, corrections and standardisation procedures to be traced back to the initial export. This approach ensured a clear separation between the raw and processed data and improved the methodological transparency, auditability and reproducibility of the bibliometric analysis.

### Conflict-resolution method

The conflict-resolution followed a multi-stage selection process. Duplicate records were identified using DOI, title, author names and year of publication. When metadata differed slightly between duplicated records, the DOI and title were treated as the primary matching criteria. Duplicate records were removed before the substantive screening stage.

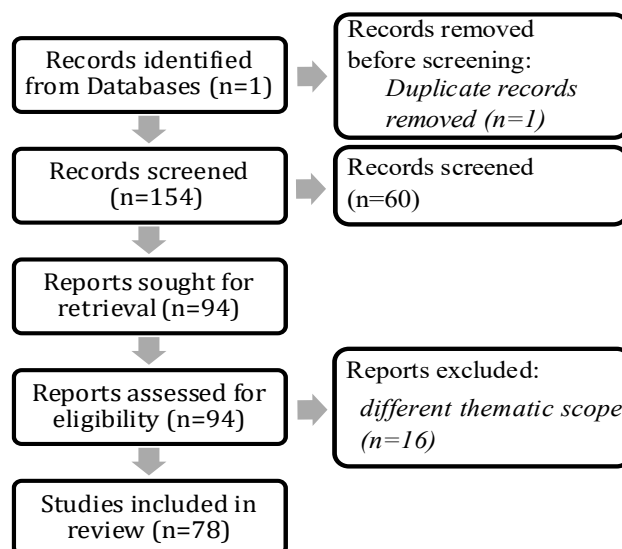
The next step involved title and abstract screening. At this stage, each record was assessed against the predefined inclusion and exclusion criteria. Records were retained if the title, abstract or keywords indicated a relationship with manufacturing, production operations, technical information processing, engineering data, decision support systems, operational decision-making or data-driven manufacturing management. Records were excluded when they were clearly unrelated to the review scope.

Subsequently, full-text eligibility assessment was conducted for records that passed the title and abstract screening. During this stage, the full publication was checked to determine whether the study actually contributed to the topic of operational decision support in manufacturing or technological information processing. Particular attention was paid to whether the paper merely mentioned manufacturing or decision-making superficially, or whether it provided a method, model, system, framework, application or empirical insight relevant to the review.

Finally, the dataset was created by retaining only studies that satisfied the eligibility criteria after full-text assessment. The final set consisted of 78 studies. These studies formed the basis for the qualitative synthesis and bibliometric analysis.

### Reasons for literature exclusion

The relationship between the initial Scopus export, the screened records, the excluded records and the final included studies is reported in the PRISMA flow diagram in Figure 2.



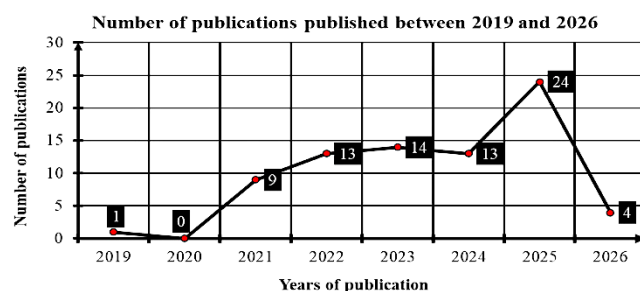
**Fig. 2 Literature screening approach**

**Alt text:** PRISMA flow diagram showing record identification, screening, retrieval, eligibility assessment, and 78 studies included in the review.

Initially, a total of 154 articles related to technical information processing and decision models were identified. One duplicate record was found in the retrieved dataset. After the screening process, a total of 60 records were excluded due to their lack of relevance to the subject of the present study. The search procedure resulted in a dataset of 94 articles published between 2019 and 2026. Following the screening procedure based on the PRISMA method, 16 records were excluded. The excluded records comprised studies related to biological sciences (5), animal farming and waste management (5), and healthcare (6). As a result, the final dataset consisting of 78 studies provided a thematically coherent basis for the analysis of research linking technological information processing with operational decision support in manufacturing.

### Final literature dataset

The chronological distribution of the 78 articles related to technical information processing and decision models is presented in Figure 3.



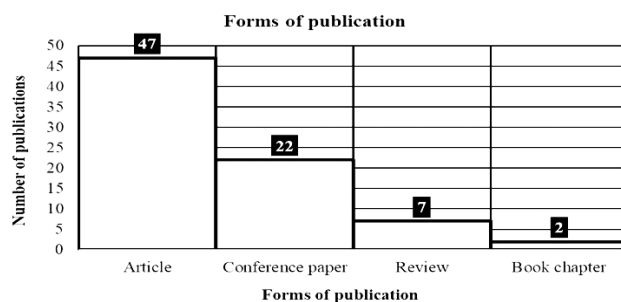
**Fig. 3 Distribution of the 78 publications in technical information processing and decision models (2019-2026)**

**Alt text:** See main text.

The chronological distribution of publications indicates that research on technical information processing and decision models was present throughout the entire analyzed period, although its intensity varied from year to year. The highest number of publications was recorded in 2025 (24 papers), which suggests a noticeable increase in research interest in this area. Relatively high publication activity was also observed in 2024 (13 papers), 2023 (14 papers) and 2022 (13 papers). A lower publication output was observed between 2019 and 2021, with a total of 10 publications.

Between 2021 and 2024, 40 publications related to the processing of technical and technological information in operational decision-support models were identified. This represents 30 more publications than in the 2019-2021 period. Increase in publications in the years 2021-2024 suggests that this period marked the strongest development of research within the examined field. A significant increase in publications in 2025 (24 publications) indicates growing interest in the field of information processing systems applied to decision-making models.

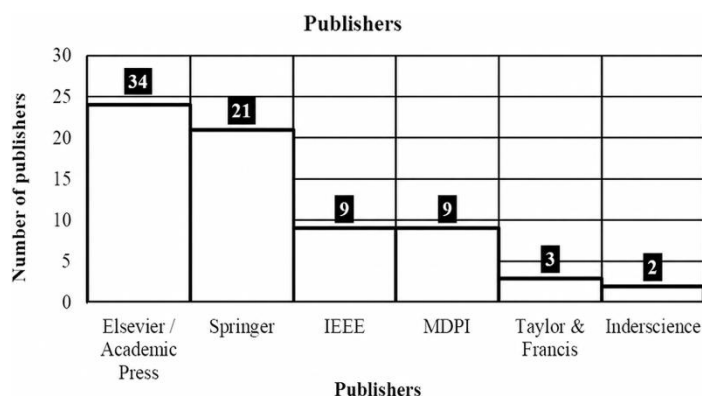
The distribution of publication types is presented in Figure 4. The largest number of publications were articles, with 47 records, representing (60.25%) of the publication types in the collected dataset of 78 literature items. Conference papers ranked second, with 22 records – accounting for (28.21%). The smallest shares were observed for reviews, with 7 records (8.97%), and book chapters, with 2 records (2.56%).



**Fig. 4 Forms of publication (2019-2026)**

**Alt text:** Bar chart showing publication forms: 47 articles, 22 conference papers, 7 reviews, and 2 book chapters.

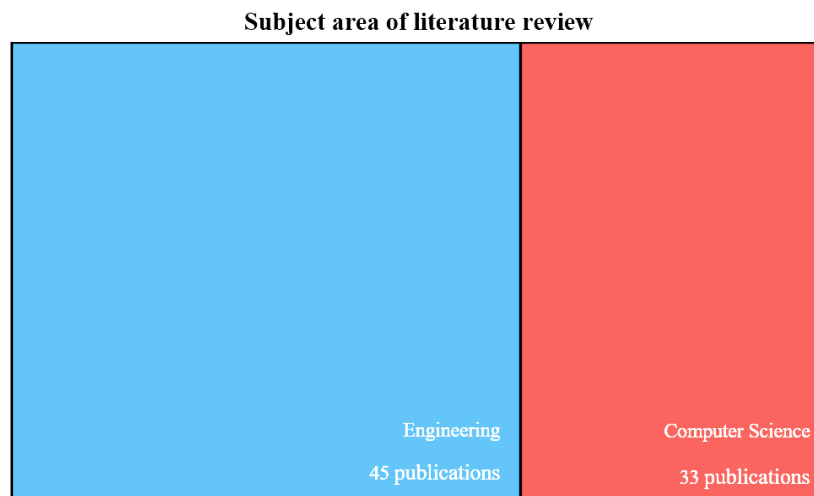
The most frequently represented publishing groups in the analysed dataset were *Elsevier/Academic Press* (34 publications), *Springer* (21 publications), *IEEE* and *MDPI* (18 publications in total), *Taylor & Francis* (2 publications), and *Inderscience* (2 publications). The publisher structure of the analysed dataset is shown in Figure 5.



**Fig. 5 Publishers (2019-2026)**

**Alt text:** Bar chart showing that Elsevier/Academic Press and Springer were the most frequent publishers in the reviewed dataset.

The subject-area structure of the analysed literature is presented in the Figure 6. The largest share of publications belongs to *Engineering* (45 publications). The second major subject area is *Computer Science* (33 publications).



**Fig. 6 Subject area of literature review**

**Alt text:** Treemap showing that Engineering was the dominant subject area, followed by Computer Science.

The distribution indicates that the analysed topic is mainly located at the intersection of engineering and computer science. The dominance of Engineering suggests that the reviewed studies are strongly related to production, manufacturing, technical information processing, and operational decision-support problems. At the same time, the significant share of Computer Science highlights the role of computational methods, data processing, artificial intelligence, and information systems in this research area.

## CONTENT ANALYSIS

At this stage of the study, a detailed review of a wide range of identified scientific publications is carried out in the field of decision-making models and information processing systems. The content analysis is focused on understanding how modern information processing systems are integrated into decision-making models. The aim of the analysis is to identify the current state of knowledge and future development perspectives of information systems supporting operational decision-making. For this purpose, four areas were selected for analysis.

- 1) Benefits of decision models and technical information processing systems in manufacturing enterprises.
- 2) Challenges of decision models and technical information processing systems in manufacturing enterprises.
- 3) Technological progress of decision models using information processing systems.
- 4) Factors influencing the implementation of decision models and information processing systems in manufacturing enterprises.

### **Benefits of decision models and technical information processing systems in manufacturing enterprises**

The implementation of information processing systems in manufacturing enterprises is associated with numerous benefits, but also with a number of challenges. This subsection reviews a body of research that examines the benefits and challenges related to the implementation of information systems and decision-making models in enterprises.

The reviewed studies indicate that the main benefit of decision models and technical information processing systems lies in their ability to transform dispersed engineering and production data into opera-

tionally useful decision premises [1-55]. This transformation is visible at several levels of manufacturing activity. It begins with the extraction of information from technical documentation [17-42, 48]. It then extends to process planning, production control, quality assurance and lead time prediction [45, 46, 47, 48, 49, 50]. Scheibel, Mangler and Rinderle-Ma report a recall value of over 88% for the extraction of dimension sets. It suggests that a large part of dimensioning information can be extracted automatically, although the method does not yet provide complete extraction accuracy. The study is important because it connects drawing interpretation with a specific downstream decision area, namely inspection and quality-control preparation [42].

A similar benefit is visible in the work of Villena Toro, Wiberg and Tarkian [49]. The authors propose OCR-based processing of engineering drawings to automate the preparation of production quality control. Their eDOCr tool separates drawing content into information blocks, dimensions and GD&T-related information. The extracted data are then converted into a structured format. The reported average results are 90% precision and recall in detection, 94% F1-score in recognition, and 8% character error rate. In the detailed evaluation on seven engineering drawings, the average values were  $RTD = 0.89$ ,  $PTD = 0.92$ ,  $F1 = 0.94$  and  $CER = 0.080$ . However, the results also varied between drawings. This means that the method is promising, but its performance still depends on drawing type and layout quality [49]. Villena Toro and Tarkian report a text recall of 93.75% and a character error rate below 1% in a benchmark using drawings from different sources. In their threshold analysis, the best reported configuration for one setting reached 93.75% recall, 96.15% precision, 86.38% IoU, 0.73% CER and 99.27% character recall. This is stronger than the earlier eDOCr results in terms of character recognition error. It also shows the direction of progress from OCR-only extraction toward OCR combined with vision-language models [48].

From the perspective of the present article, these studies show that decision support in production begins before scheduling, optimization or shopfloor control. It begins when technical information is made machine-readable and reusable. Dimensions, tolerances, material symbols, surface requirements and title-block data influence later decisions. They affect inspection planning, process selection, routing, resource allocation and production feasibility. The benefit of information processing systems is therefore not limited to faster reading of documents. Their real value appears when extracted information becomes part of a broader decision chain.

A second group of benefits concerns process planning and production preparation. Wagner et al. present a digital twin for process planning [50]. The system automatically analyses the product, determines production processes and selects appropriate resources by linking product, process and resource information. This is one of the strongest conceptual examples of integration between information processing and decision-making. However, the article does not report a clear numerical gain such as percentage reduction in planning time, cost or lead time. The authors state that the DTPP demonstrated superior performance, especially in the time needed to complete multiple valid process-planning tasks, but they do not provide a quantified before–after comparison in the form of a percentage improvement [50].

De Simone et al. propose a Masterplan-based system for lead time prediction in SMEs [5].

Their framework treats each order as a project composed of interrelated tasks. It integrates task duration, workload, workforce capacity and machine capacity into a planning structure. The authors show a numerical feasibility example in which a task with a predicted workload of 100h over 2 weeks is distributed as 50h per week [5].

A related quantitative contribution is provided by Rokoss et al. in delivery-time prediction for small-batch production companies [40]. In one case study, the authors show that a machine-learning approach supported by domain-knowledge features can strongly reduce prediction errors. The baseline based on mean delivery time produced  $RMSE = 12.15$  days and  $MAE = 10.42$  days. The process-planning department achieved  $RMSE = 5.87$  days and  $MAE = 3.83$  days. The ML model with planned times achieved  $RMSE = 5.56$  days and  $MAE = 3.98$  days. The ML model without planned times but with domain-knowledge features achieved  $RMSE = 7.73$  days and  $MAE = 6.03$  days, while the model without domain-

knowledge features achieved RMSE = 9.47 days and MAE = 7.48 days. The authors also state that, in one use case, the forecast error measured by NRMSE can be reduced by about two-thirds compared with the previous method [40].

This evidence is important for the present article. It suggests that the value of decision models depends not only on the algorithm, but also on the information used as input. Domain-knowledge features and information on the current state of the manufacturing system reduce prediction error. This highlights that production decision models require structured operational and contextual data, not only historical averages.

Process mining studies show a further benefit. Botelho et al. combine process mining and machine learning to predict the remaining time of production orders [3]. Their approach uses event logs to represent the actual execution of production processes. It then combines annotated transition systems with machine learning regressors. The authors report that, across three tested products, the hybrid model consistently obtained the lowest MAE and improved prediction accuracy by up to 12% compared with baseline and state-of-the-art machine-learning models. The model can support the planner while the production order is still in progress. It can help identify delays, deviations and rescheduling needs before the final delivery date is missed. The benefit therefore lies in the conversion of event data into time-sensitive operational decisions [3].

### **Challenges of decision models and technical information processing systems in manufacturing enterprises**

The literature review also points to a number of persistent challenges in the operation of information processing systems and decision models. The first and most fundamental challenge is data fragmentation [7, 30, 50]. Manufacturing data are dispersed across: *technical drawings, CAD files, BOMs, routings, ERP systems, PLM systems, MES systems, event logs and shopfloor databases* [7, 9, 14, 26, 30, 42, 50]. In many companies, part of the relevant knowledge is not stored in any digital system. It remains implicit in the experience of technologists, planners and operators [5, 9, 50].

Meyers et al. explicitly identify this problem in their study on knowledge graphs for ad hoc analysis in manufacturing [30]. They indicate that industrial analytics is limited by heterogeneous data, data silos, lack of formalized knowledge and limited reasoning capabilities. Their framework is designed to combine data, information and knowledge in a manufacturing context.

The substantive contribution of the paper is architectural and methodological. The value lies in the ability to structure data, information and knowledge in a reusable framework, not in a measured percentage improvement [30].

This challenge is central to the present research. A decision model cannot operate effectively on isolated data items [30, 50]. A dimension extracted from a drawing must be linked with a feature [42, 48, 49]. The feature must be linked with a process [47, 54, 50]. The process must be linked with a resource [28]. The resource must be linked with availability, capacity, cost and risk [5, 40, 45, 50]. Without such connections, the company may have data, but it does not have decision knowledge [7, 30, 50].

The second challenge concerns the reliability of technical information extraction [17-42, 25, 48]. Engineering drawings are complex documents [32, 48]. They include geometry, dimensions, tolerances, GD&T symbols, notes, tables and title blocks [1, 16, 17, 25, 42, 48]. Generic OCR methods are not designed for this type of content [44, 48, 49]. Villena Toro, Wiberg and Tarkian address this problem by developing a dedicated OCR approach for engineering drawings [48, 49]. Their study confirms that technical drawings require specialized segmentation and recognition procedures [48, 49]. The quantitative results also show this clearly. Even though the average eDOCr values were high, with RTD = 0.89, PTD = 0.92, F1 = 0.94 and CER = 0.080, the "Gripper" drawing reached only RTD = 0.73 and PTD = 0.80 [12]. This variation highlights that drawing layout and symbol representation still affect reliability.

This has a direct consequence for decision models. If a tolerance is extracted incorrectly, the inspection plan may be incorrect [42, 48, 49]. If the material information is not recognized, the process route may

be incomplete [16, 17, 55]. If the drawing revision is misread, the production system may use outdated technical information [14, 26]. The quality of the decision model therefore depends on the quality of information extraction [16, 17, 42, 48, 49].

The third challenge is incomplete automation of process planning [9, 47, 50, 54]. Wagner et al. show that process planning still requires substantial expert knowledge [50, 52]. They also indicate that current research has not fully achieved complete process planning automation. Process planning requires product requirement analysis, process identification, process sequencing, resource selection and performance-parameter determination [50, 52]. These phases are difficult to automate because they involve technical rules, resource constraints and production-specific knowledge [9, 47, 50, 54].

This point is important for the research gap. It would be incorrect to claim that digital twins, CAPP systems or AI-based systems already solve the full problem of production preparation [47, 50, 54]. The more accurate conclusion is that current systems support selected parts of the decision process [45]. They are promising, but they remain partial and context-dependent [45].

The fourth challenge concerns SMEs [5, 38, 40]. De Simone et al. show that SMEs often do not use sophisticated ERP systems [5]. The reasons include cost, complexity and difficulty of implementation [5]. In such companies, lead time is often estimated by employees on the basis of experience and intuition. This approach is practical, but it is also prone to error [5, 40]. The implementation of decision models cannot be discussed only in the context of advanced digital factories [5, 7]. Many companies first need a structured data model [5, 9, 30]. They need definitions of tasks, workloads, resources, capacities and order states [5, 9]. Without this basic structure, AI and predictive models cannot deliver reliable support [3, 5].

The fifth challenge is model fragmentation [3, 30, 45, 50]. Botelho et al. point out that some methods focus on process structure but lack predictive functionality [3]. Other methods rely mainly on data-driven prediction and ignore process logic. Their hybrid approach attempts to overcome this by combining process mining with machine learning and optimization [3]. This is not only a conceptual statement. The hybrid model improved prediction accuracy by up to 12%, which indicates that combining process structure with data-driven prediction can produce measurable benefits [3]. This is also visible across the broader literature:

- drawing-processing studies are strong in extraction [17-42, 25, 48],
- process-planning studies are strong in product-process-resource modelling [9, 47, 50, 54],
- process-mining studies are strong in execution analysis [3, 20],
- lead-time studies are strong in operational prediction [5, 40].

However, these layers are often not connected [30, 45, 50]. This limited integration is one of the main challenges addressed by the present article [17, 30, 50].

### **Technological progress of decision models using information processing systems**

The literature indicates significant technological advances in the application of information systems and decision models in industrial processes [42-50]. Earlier approaches focused mainly on manual analysis, rule-based procedures and isolated data processing [9, 32, 54]. More recent studies use: *OCR, computer vision, deep learning, vision-language models, process mining, knowledge graphs, ontologies* and *digital twins* [3, 15, 20-36, 44, 50, 55]. This progression does not only concern the sophistication of algorithms. It also concerns the way in which technical and operational data are represented and used [17, 30, 50]. In engineering drawing processing, technological progress can be observed in the transition from simple text recognition to structured information extraction [1, 16, 17, 25, 42, 44, 48, 49, 55].

Xie et al. use graph neural networks to classify manufacturing methods from engineering drawings [53]. Their study suggests that drawings can be interpreted not only as images, but also as structured representations of manufacturing-relevant features [53]. The work extends drawing analysis toward manufacturing-method classification [53].

Khan et al. extend this direction by using document understanding and vision-language approaches for automated information extraction from engineering drawings [15, 16, 17]. Their framework extracts several types of information, including GD&T, dimensions, materials, notes, surface finish information and title-block content [16, 17]. These studies show that technical information processing is moving from digitisation toward semantic interpretation [16, 17, 48, 55]. The aim is no longer only to read text from a drawing. The aim is to identify what the extracted information means for manufacturing, inspection or process planning [53, 55]. The eDOCr2 results provide the strongest quantified confirmation of this progress. Compared with eDOCr, eDOCr2 improved detection precision from 70% to 96%, reduced CER from 8% to 0.7%, and reduced processing time from 53.5s to 10.7s [48].

A more advanced technological stage is visible in digital twin applications for process planning. Wagner et al. propose a digital twin architecture that includes a knowledge representation, a central database, simulation-based process planning and interfaces to decision-making systems [50]. The system is designed to analyse product data, identify process alternatives, select resources and assess performance parameters. The system does not merely store CAD data. It interprets product properties as process requirements. It compares these requirements with resource skills. It then supports the selection of feasible process plans. This is a significant step toward decision-oriented information processing [20, 50].

Knowledge graphs represent another important technological direction. Meyers et al. propose a framework for ad hoc analysis in manufacturing based on knowledge graphs [30]. Their approach is intended to connect heterogeneous data sources and formalize knowledge about the manufacturing system. This is important because production decisions are relational [30, 50].

A material affects a process [47, 55]. A process affects quality [42, 49, 50]. A resource affects capacity [5]. Capacity affects lead time [40]. Lead time affects customer delivery performance [5, 40]. Knowledge graphs make such relations explicit [30]. They therefore provide a foundation for more advanced decision models [30, 50].

In production planning and control, technological progress is visible in the use of process mining and predictive models [3, 5, 20, 40]. Botelho et al. integrate process mining and machine learning for remaining time prediction [3]. This allows the current state of a production order to be used as input for prediction. Their hybrid model achieved the lowest MAE across the three tested products and improved prediction accuracy by up to 12% relative to benchmarked models [3]. This shifts the role of decision support. The model does not only describe past performance [3, 20]. It estimates future execution time [3]. This enables earlier intervention in production planning and control [3, 5, 20, 40].

The technological trajectory can therefore be described as follows. First, technical and operational data are digitised [17-42]. Second, they are structured [16, 17, 30, 49, 55]. Third, they are semantically represented [30, 50]. Fourth, they are used in prediction, simulation or optimization [20-50]. Fifth, they support decisions [3, 5, 40, 45, 50]. The literature shows strong progress in the first four stages. The final stage, namely coherent decision integration across several production functions, remains less mature [30, 45, 50].

### **Factors influencing the implementation of decision models and information processing systems in manufacturing enterprises**

The first implementation factor is data readiness [42-55]. Decision models require structured and reliable input data [3, 30, 45, 50]. Drawing-based systems require readable documentation [17-42]. Process-planning systems require product, process and resource data [9, 47, 50, 54]. Process-mining systems require event logs [3, 20]. Lead-time models require information about tasks, workload, resources, capacities and order status [5, 40].

The second factor is the maturity of technical documentation and engineering data [17-42, 48]. Studies on engineering drawing processing show that the quality and format of drawings affect the performance of extraction systems [14, 26, 29, 44, 48, 49]. Raster drawings scanned drawings and non-standard draw-

ing layouts create additional difficulties [14, 26, 29, 32, 44]. Systems based on OCR and computer vision therefore require preprocessing, segmentation and validation [1, 16, 29, 44, 48, 49]. The quantitative evidence supports this point. eDOCr achieved average values of  $RTD = 0.89$ ,  $PTD = 0.92$ ,  $F1 = 0.94$  and  $CER = 0.080$ , but the results varied substantially across drawings [12]. eDOCr2 improved these values in several dimensions, reducing CER to 0.7% and runtime to 10.7 s in the comparison with eDOCr [48].

The third factor is semantic readiness [30, 50]. Data must be connected with meaning [30, 50]. Wagner et al. show that process planning requires knowledge about products, processes, resources, skills and performance parameters [50]. CAD, CAM and CAPP tools may reduce manual effort, but they do not remove the need for knowledge representation [50, 54]. This is a key implementation issue. A company may have CAD files, ERP records and machine data [7, 30]. This does not mean that it has a decision-support system. The data must be mapped into a structure that reflects product – process – resource relations. Only then can they support process selection and resource allocation [30, 50].

The fourth factor is the availability of operational data [3, 5, 6, 7, 40]. Process mining requires event logs with cases, activities, timestamps and resources [3, 20]. Botelho et al. show that production orders can be represented as cases in an event log [3]. Activities, machines, timestamps and quantities become the basis for predictive monitoring [3]. Their results show that, when such data are available and combined with process-mining structures and machine-learning regressors, prediction accuracy can improve by up to 12% [3]. If such data are incomplete or inconsistent, process mining loses reliability [3, 20]. If repeated operations are not recorded correctly, the process model may not represent the real execution logic [3, 20]. If resource data are missing, workload and bottleneck analyses become limited [3, 5, 20].

The fifth factor is organizational fit [5, 7, 40]. De Simone et al. emphasize that many SMEs cannot implement complex ERP-based solutions [5]. Their Masterplan framework is designed to be simpler, more adaptable and suitable for MTO and ETO environments. This point is important because implementation depends on the context of the enterprise [5, 7, 40]. A large manufacturer may implement a complex PLM-ERP-MES architecture [7, 30, 50]. An SME may first need a lightweight planning and monitoring system [38, 40]. In both cases, the principle remains the same. Data must be structured in a way that supports decisions [30, 50].

The sixth factor is human involvement [5, 17, 25, 38, 40, 50]. The literature does not support the view that decision models eliminate specialists [5, 17, 38, 50]. Rather, they change the role of specialists [5, 7, 38, 50]. Technologists, planners and operators remain responsible for validation, interpretation and final decisions [5, 38, 40, 50]. This is particularly relevant to the present article. In production preparation, the system should not replace the technologist [38, 47, 50]. It should support the technologist by extracting information, structuring alternatives, checking feasibility and exposing constraints [3, 17, 47, 50]. The final technological decision still requires expert judgment [5, 45, 50].

The seventh factor is economic justification [5, 9, 40, 45]. Decision-support systems are more likely to be implemented when they produce measurable effects [5, 40, 45]. In the reviewed set, the clearest measurable effects include the 92.14% reduction in dimension extraction time reported by Agritania and Isnaini [1], the reduction of NRMSE by about two-thirds reported by Rokoss et al. [40], the improvement of remaining-time prediction accuracy by up to 12% reported by Botelho et al. [3], and the reduction of eDOCr2 processing time from 53.5s to 10.7s reported by Villena Toro and Tarkian [48]. The implementation argument is therefore not only technical. It must also be economic and organizational [5, 7, 45].

## QUANTITATIVE ANALYSIS

This section presents a quantitative analysis of technical information processing systems in the application of decision models to operational processes. Based on an extensive set of articles retrieved from the Scopus database (78 publications), the study provides an in-depth analysis of the current state of

innovation and integration in the developing field of deep learning, decision trees, and information processing models.

### Normalisation and cleaning keywords procedure

Keyword normalisation was performed before constructing the co-occurrence network.

The normalisation procedure included:

- standardising singular and plural forms,
- unifying British and American spelling variants,
- harmonising hyphenated and non-hyphenated forms,
- merging abbreviations with their full expressions.

Keywords as “decision support system” and “decision support systems” were treated as one conceptual category, and abbreviations such as “DSS” were mapped to the corresponding full term where the meaning was unambiguous. Near-synonymous terms were merged only when they referred to the same concept within the context of the analysed literature. Terms were not merged when they represented analytically distinct concepts. For example, “decision making” and “decision support systems” were treated as related but not automatically identical, unless the exported metadata clearly used them interchangeably in the same conceptual sense. This conservative approach was adopted to avoid excessive aggregation and loss of interpretive detail.

General, vague or non-informative terms were removed from the keyword set when they did not contribute to the interpretation of the thematic structure. Such terms included overly broad expressions, publisher-related terms, generic methodological labels without analytical value, and isolated terms unrelated to the research question. The final cleaned keyword set was then used to generate the VOSviewer co-occurrence map.

### VOSVIEWER ANALYSIS

Using the VOSviewer keyword mapping software, the following indicators were assessed:

- **cluster** – indicates the cluster number to which VOSviewer assigns thematically related groups of terms identified in the literature,
- **links** – the number of direct connections between a given term and other terms (the higher the value, the more keywords are connected with that term),
- **total link strength** – the cumulative strength of all links of a given term (this indicator suggests how strongly the term is embedded in the network),
- **occurrences** – the number of occurrences of a given term in the analysed literature database (it indicates how many times the term appeared in the analysed records, for example in keywords),
- **avg. pub. year** – the average publication year of the documents in which a given term appears,
- **avg. citations** – the average number of citations of the publications in which a given term appears.

### Minimum occurrence threshold for keywords

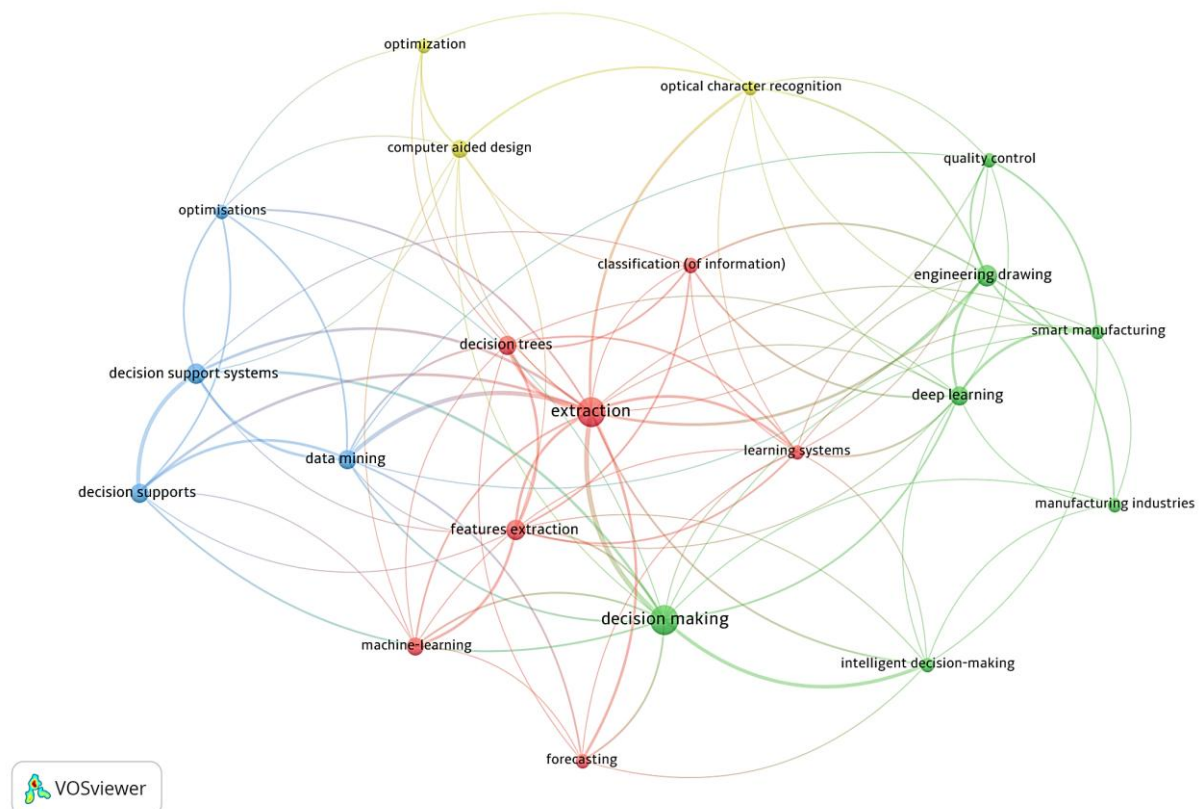
The minimum occurrence threshold for keywords was set at four occurrences. This value was selected as a methodological compromise between inclusiveness and interpretability. A lower threshold would have produced a very dense network containing many isolated or weakly connected terms, which would reduce the clarity of the thematic structure. A higher threshold would have removed too many specialised terms, including keywords important for emerging research directions such as engineering drawing analysis, digital twins, knowledge graphs, feature extraction or data-driven production planning.

The threshold of four occurrences allowed the analysis to retain keywords that appeared repeatedly in the dataset while excluding accidental, highly specific or one-off terms. This was particularly important because the dataset combined studies from several related but not identical research streams, including manufacturing decision support, technological information processing, machine learning, production planning, process mining and semantic data integration.

The selected threshold also provided a manageable number of nodes for visual interpretation in VOSviewer. The objective of the bibliometric map was not to visualise every keyword present in the dataset, but to identify the main thematic concentrations and relationships between recurring concepts. Therefore, the threshold of four keywords was chosen to balance analytical coverage with readability of the network.

### Co-occurrence analysis map

For the co-occurrence analysis, a minimum threshold of four keyword occurrences was applied to the analysed set of 78 articles. The unit of analysis was based on index keywords. Out of 819 keywords, 24 keywords met the adopted occurrence threshold. During the construction of the co-occurrence map, synonymous or closely related keyword variants were standardised: decision making (decisions makings removed), decision support systems (support systems removed), and features extraction (feature extraction removed). The keyword co-occurrence map for the analysed literature dataset is presented in Figure 7.



**Fig. 7 Type of analysis: Co-occurrence, Index keywords, minimum number of occurrences of a keyword: 4 (of the 819 keywords, 24 meet the threshold)**

**Alt text:** VOSviewer keyword co-occurrence map showing clusters around extraction, decision making, data mining, and smart manufacturing.

### The most strongly connected keywords related to decision models and information processing systems

The nodes *extraction* and *decision making* appear among the most prominent elements of the map. This visual observation is supported by bibliometric indicators. *Decision making* recorded 23 occurrences, while *extraction* recorded 16 occurrences. In terms of network connectivity, *extraction* recorded 37 links and *decision making* recorded 31 links. Both terms reached the same total link strength value of 80. This indicates that *extraction* and *decision making* are not only frequent terms, but also highly connected elements of the keyword co-occurrence network.

The ten most frequent keywords associated with *extraction* and *decision making* are presented in the Table 1 and Table 2.

**Table 1**  
***The ten most frequent keywords associated with extraction***

| No. | Keyword                       | ID  | Cluster | Occurrences | Link strength extraction |
|-----|-------------------------------|-----|---------|-------------|--------------------------|
| 1   | decision making               | 170 | 3       | 23          | 6                        |
| 2   | data mining                   | 163 | 3       | 7           | 5                        |
| 3   | decision trees                | 180 | 2       | 7           | 4                        |
| 4   | decision support systems      | 175 | 3       | 8           | 3                        |
| 5   | engineering drawing           | 242 | 1       | 9           | 3                        |
| 6   | features extraction           | 268 | 2       | 8           | 3                        |
| 7   | forecasting                   | 285 | 4       | 4           | 3                        |
| 8   | knowledge extraction          | 395 | 3       | 3           | 3                        |
| 9   | learning systems              | 414 | 2       | 4           | 3                        |
| 10  | multi-objectives optimization | 494 | 3       | 3           | 3                        |

**Table 2**  
***The ten most frequent keywords associated with decision making***

| No. | Keyword                     | ID  | Cluster | Occurrences | Link strength decision making |
|-----|-----------------------------|-----|---------|-------------|-------------------------------|
| 1   | extraction                  | 255 | 3       | 16          | 6                             |
| 2   | intelligent decision-making | 374 | 2       | 4           | 4                             |
| 3   | decision support systems    | 175 | 3       | 8           | 3                             |
| 4   | data mining                 | 163 | 3       | 7           | 2                             |
| 5   | deep learning               | 186 | 1       | 7           | 2                             |
| 6   | features extraction         | 268 | 2       | 8           | 2                             |
| 7   | forecasting                 | 285 | 4       | 4           | 2                             |
| 8   | knowledge extraction        | 395 | 3       | 3           | 2                             |
| 9   | machine-learning            | 435 | 4       | 6           | 2                             |
| 10  | artificial intelligence     | 35  | 3       | 3           | 1                             |

The analysis of direct keyword links suggests that *extraction* and *decision making* are closely connected in the co-occurrence network. The strongest link for *extraction* was observed with *decision making* (link strength = 6, occurrences = 23). The strongest link for *decision making* was also observed with *extraction* (link strength = 6, occurrences = 16). This reciprocal relationship indicates that both terms form a central thematic connection in the analysed literature sample.

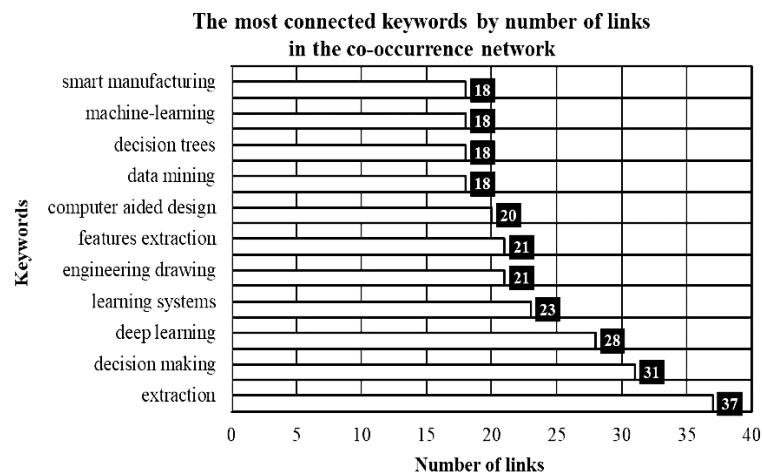
The keyword *extraction* is associated with *data mining* (link strength = 5, occurrences = 7), *decision trees* (link strength = 4, occurrences = 7), and *decision support systems* (link strength = 3, occurrences = 8). This suggesting that extraction-oriented studies are mainly linked with analytical, classification, and data-processing methods.

In turn, *decision making* is directly related to *intelligent decision-making* (link strength = 4, occurrences = 4), *decision support systems* (link strength = 3, occurrences = 8), *data mining* (link strength = 2, occurrences = 7), and *deep learning* (link strength = 2, occurrences = 7). In the analysed literature sample, the term *decision making* is linked to both *machine-learning* (link strength = 2, occurrences = 6) and *artificial intelligence* (link strength = 1, occurrences = 3). However, the strength of these links is relatively low. This means that machine learning and artificial intelligence methods appear in the context of decision-making, but they do not yet form the dominant stream in the analysed literature. Rather, they indicate an emerging research direction than a well-established thematic area. The Table 1 and 2 confirms that the relationship between extraction and decision making is not incidental, but represents one

of the strongest direct connections in the keyword co-occurrence structure. The keyword *decision making* occurred 23 times, representing approximately 29.49% of the analysed dataset (23 times/78 articles).

This was one of the highest occurrence values in the analysed keyword network.

The most connected keywords by number of links in the co-occurrence network are presented in Figure 8.

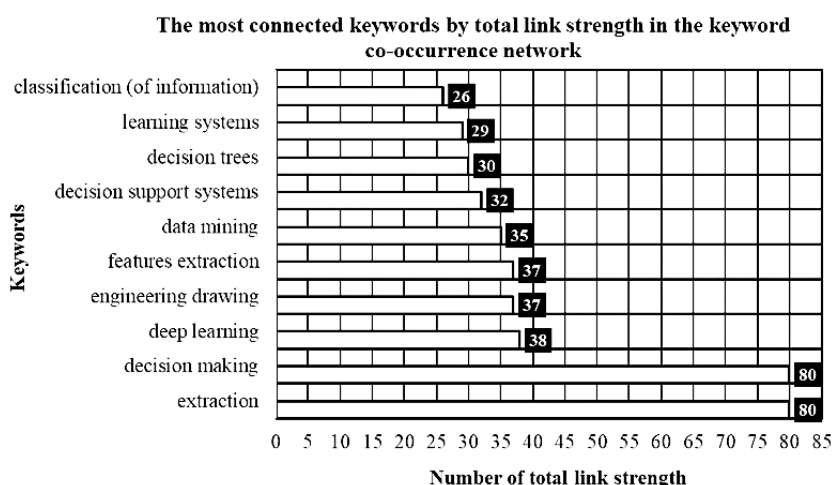


**Fig. 8 The most connected keywords by number of links in the co-occurrence network**

**Alt text:** Horizontal bar chart showing extraction as the most connected keyword, followed by decision making and deep learning.

The Figure 8 suggests the keywords with the highest number of links. Keyword *extraction* has the highest number of links, with 37 direct connections. It is followed by *decision making* with 31 links and *deep learning* with 28 links. This indicates that extraction is the most connected keyword in the network. It has a significant role in linking different thematic areas, such as *deep learning* (links = 28), *learning systems* (links = 23), *engineering drawing* (links = 21), and *features extraction* (links = 21).

The most connected keywords by total link strength in the keyword co-occurrence network are presented in Figure 9.



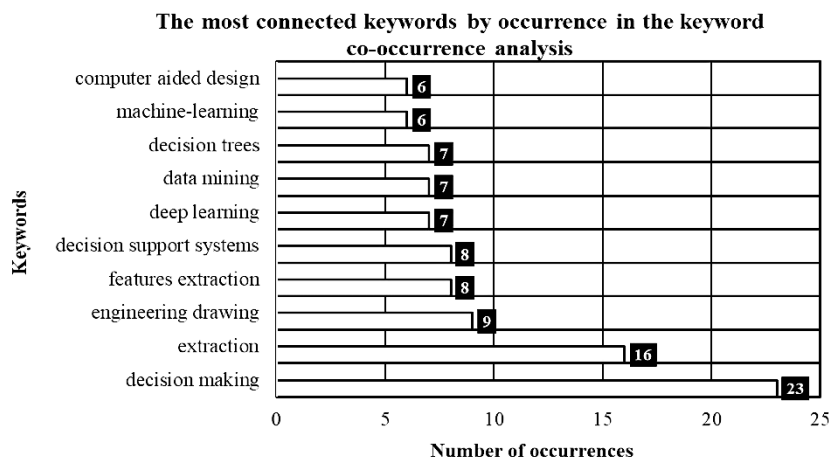
**Fig. 9 The most connected keywords by total link strength in the keyword co-occurrence network**

**Alt text:** Horizontal bar chart showing total link strength; extraction and decision making are highest, both with 80.

The Figure 9 presents the keywords with the highest total link strength. Again, *extraction* is the dominant term, with a total link strength of 80. *Decision making* is second, with a total link strength of 80. This highlights that the relationship structure of the analysed literature is strongly built around information

extraction and decision-oriented approaches. Terms related to information processing, show strong connectivity in the keyword co-occurrence network: *deep learning* (total link strength = 38), *engineering drawing* (total link strength = 37), *features extraction* (total link strength = 37), and *data mining* (total link strength = 35).

The most connected keywords by occurrence in the keyword co-occurrence analysis are presented in Figure 10.



**Fig. 10 The most connected keywords by occurrence in the keyword co-occurrence analysis**

**Alt text:** See main text.

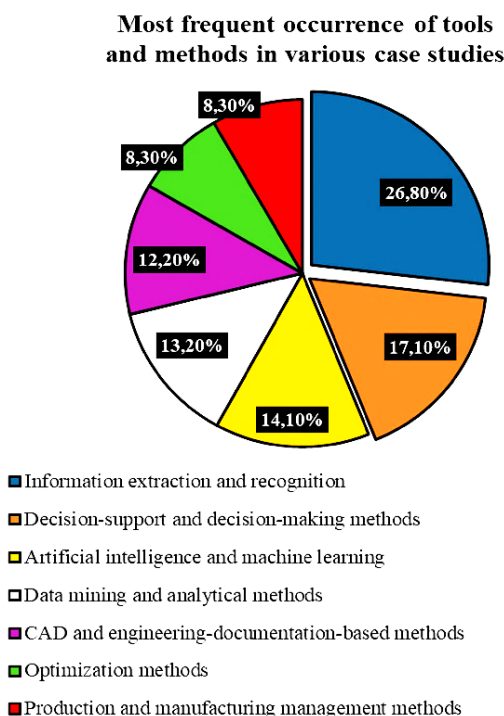
The occurrence analysis indicates that *decision making* and *extraction* are the most frequent keywords in the analysed dataset. *Decision making* recorded 23 occurrences, while *extraction* recorded 16 occurrences. When related keywords are considered together, information-processing oriented terms show a higher cumulative presence than decision-oriented terms. The keywords *engineering drawing* (occurrences = 9), *features extraction* (occurrences = 8), *deep learning* (occurrences = 7), *data mining* (occurrences = 7), *decision trees* (occurrences = 7), *machine-learning* (occurrences = 6), and *computer aided design* (occurrences = 6) also show a strong presence in the analysed network. This suggests that technical information processing is a stronger represented topic area in the analyzed literature than operational decision support.

The higher cumulative occurrence of information-processing-oriented keywords does not necessarily indicate that information processing dominates decision-making research in general. Rather, it reflects the thematic structure of the analysed literature sample. The results suggest that the selected publications place stronger emphasis on the acquisition, extraction, recognition, and processing of technical information than on the formal development of decision models. Therefore, the findings should be interpreted as evidence of a strong representation of information-processing methods within the analysed sample, not as a general conclusion about the entire research field.

### The most frequent occurrence of tools and methods in various case studies

Based on the most keywords occurrences (Figure 10), developed the most frequent occurrence of tools and methods in different case studies (Figure 11).

The Figure 11 presents the cumulative occurrence of tool- and method-related keyword groups in the analysed literature sample. The largest share is represented by information extraction and recognition methods, accounting for 26.80% of the classified occurrences.



**Fig. 11 The most frequent occurrence of tools and methods in various case studies**

**Alt text:** See main text.

This group includes terms related to extraction, feature extraction, object recognition, text recognition, optical character recognition, and information retrieval. The second largest group is decision-support and decision-making methods, with 17.10%. This highlights that decision-oriented approaches are also clearly present in the analysed dataset, although their share is lower than that of information extraction and recognition methods. Artificial intelligence and machine learning account for 14.10%, which suggests that AI-based techniques support both information processing and decision-oriented research. The remaining groups include data mining and analytical methods with 13.20%, CAD and engineering-documentation-based methods with 12.20%, and two smaller groups: optimization methods and production and manufacturing management methods, each with 8.30%.

## THE INTERPRETATION OF CLUSTERS AND KEYWORDS TO THE RESEARCH QUESTIONS

The interpretation of clusters and keywords provides a quantitative basis for answering the main research question concerning the integration of information processing systems with operational decision-making models in manufacturing. The co-occurrence structure indicates that the analysed literature is organised around two strongly connected but still partly separated thematic orientations. The first orientation is related to technological information processing, including extraction, engineering drawing, features extraction, deep learning, data mining, machine-learning and computer aided design. The second orientation concerns decision-related concepts, represented mainly by decision making, decision support systems and intelligent decision-making. The fact that extraction and decision making both reached the highest total link strength values confirms that the relationship between information acquisition and decision-oriented use is central to the analysed dataset. However, the distribution of keywords also shows that the literature gives stronger cumulative attention to the acquisition, recognition and processing of technical information than to the development of fully integrated operational decision-support models.

This result directly supports the identified research gap: current studies increasingly transform technical documentation and production data into structured digital information, but this information is not always connected with explicit decision models for planning, process selection, capacity assessment, quality control or production execution. Therefore, the cluster and keyword analysis confirms that

the integration of technological information processing with decision support remains a developing and insufficiently consolidated research area.

The results therefore justify the need for further research on models that connect engineering documentation, product and process data, resource capabilities, capacity constraints and execution feedback within one coherent decision-support architecture. This interpretation links the quantitative VOSviewer results with the qualitative findings of the review and strengthens the conclusion that information processing should not be treated as an isolated technical activity, but as an upstream component of operational decision support in manufacturing enterprises.

### **Stages of implementing information systems in decision-making models**

The VOSviewer analysis provides a quantitative basis for identifying how information-processing systems can be integrated with decision-support models in manufacturing enterprises. The implementation process of information systems in decision-making models may be conceptualised as a sequence of interrelated stages:

- identification of the stages of information-system implementation,
- organisational prerequisites for the effective adoption of information systems,
- expected benefits and limitations of information-system-supported decision-making.

### **Identification of the stages of information-system implementation**

Data maturity may be understood as a progressive condition for the effective integration of information processing systems with decision-making models. At the initial level, data are available in non-digital or weakly structured forms, such as paper-based drawings, scanned technical documentation, manually maintained spreadsheets, or tacit expert knowledge. At this stage, implementation efforts should primarily focus on digitisation, information extraction, data cleaning, and the transformation of dispersed information into structured datasets [2, 4, 6, 8, 10]. At the intermediate level, data are already structured but remain only partially integrated across organisational and technical systems. Such data can support rule-based or algorithmic decision-making. However, the reliability of the decision model still depends on data completeness, regular updating, and the correct interpretation of operational states. At the higher level of maturity, data are integrated across enterprise and production systems, including ERP, MES, SCM, SRM, WMS and IoT platforms. This enables broader operational visibility and supports planning, quality monitoring, supplier coordination, and more responsive production control [8, 10, 11, 12, 13].

At the most advanced level, data are not only integrated but also semantically described, synchronised, and connected with simulation, optimisation, or learning-based models. This level of maturity is required for digital twins, ontology-based decision support, reinforcement learning, and prescriptive analytics. It requires more than data availability alone. It also requires a formal representation of system states, actions, objectives, constraints, relationships, dependencies, and feedback loops. Therefore, data maturity determines whether information systems can support only descriptive reporting or whether they can be developed into predictive and prescriptive decision-support mechanisms for production operations [18, 19].

### **Organisational prerequisites for the effective adoption of information systems**

Several organisational prerequisites are required for the effective implementation of information systems in decision-making models. A fundamental condition is a clearly defined structure of decision ownership. The implementation of a decision support system requires the explicit identification of decision-makers, data providers, model validators and users responsible for acting upon system recommendations. Without such role allocation, analytically valid outputs may remain weakly connected to actual organisational decision processes [21, 22, 23, 24].

Another important condition is cross-functional collaboration. Production operations are not limited to a single organisational function, but involve technology, production planning, logistics, quality management, maintenance, procurement, human resources and finance. Therefore, decision-support implementation requires the participation of actors representing different areas of operational knowledge [27, 28, 31]. Lidberg involved managers from production, maintenance, quality, method development, information technology, production technology and human resources in order to identify industrial requirements for decision support [23]. Similarly, Japs et al. indicate that interdisciplinary understanding is essential when modelling cyber-physical systems, as insufficient system understanding may result in unidentified safety and security risks [13].

Digital competence and user readiness are also necessary for successful implementation.

Many advanced information systems require knowledge of modelling environments, data architectures, ontologies, optimisation methods and analytical tools. This creates a substantial implementation barrier, particularly in manufacturing companies with limited digital resources [33, 34, 35]. Carlin et al. note that ontology-based digital twin frameworks require knowledge of tools such as Protégé and OWL, which cannot be assumed to be available in a typical manufacturing facility [4]. A similar limitation applies to small and medium-sized enterprises, which may not have sufficient financial, technical or human resources to implement and maintain advanced ERP systems, cloud manufacturing solutions or automated production lines [33, 34, 35].

Effective change management is equally important. The integration of ERP systems, Industry 4.0 technologies and decision-support models should not be treated merely as a technical upgrade. It requires managerial commitment, workforce reskilling, standardised workflows, cross-functional coordination and an organisational culture oriented towards continuous improvement and learning. In the absence of these conditions, even technically advanced systems may remain underused or may fail to become embedded in routine operational decision-making [37, 39, 41, 43].

### **Expected benefits and limitations of information-system-supported decision-making**

The expected benefits of integrating information systems into decision-making models are significant, although they remain conditional upon the quality of data, the maturity of digital infrastructure and the organisational context of implementation. Modern information systems can improve production visibility, accelerate planning activities, increase decision consistency and support scenario-based analysis. They can also enhance resource allocation, quality control, supplier resilience, ergonomic risk assessment and maintenance-related decision-making. In this context, digital twins provide particular value by supporting layout optimisation, dynamic production planning, bottleneck identification, capacity analysis and what-if scenario testing. ERP integration, in turn, enables real-time operational visibility and strengthens cross-functional data coordination. OCR and vision-language-based systems can transform legacy engineering drawings and scanned technical documentation into structured information, which may subsequently support BIM environments, digital twins and decision-making models [46, 51, 52].

A further benefit concerns the formalisation and transparency of decision logic. MILP-based decision support systems can make strategic production allocation more explicit by linking decision variables, constraints and objective functions within a coherent optimisation model. Simulation-based optimisation can support prescriptive analytics by identifying improvement rules and prioritising operational interventions. Ontology-based approaches can standardise terminology and represent dependencies between digital twin components, data sources and decision requirements. Similarly, rule-discovery methods can reduce the need for manually defined heuristics when extracting structured elements from natural language or technical descriptions.

In this sense, the reviewed approaches contribute to the transformation of dispersed operational, technical and organisational data into structured, decision-relevant knowledge [19, 21, 24].

At the same time, the limitations of these systems must be clearly recognised. Many of the reviewed solutions are domain-specific prototypes, conceptual frameworks or case-study-based implementations. Their transferability to other production environments is therefore limited and requires adaptation of data structures, rules, performance indicators, system architecture and user workflows. For example, OCR-based systems for engineering drawings depend on document conventions, field locations, keyword structures and drawing quality. Their application to other documentation standards may require revised extraction rules, new keywords, additional field definitions and more advanced table-aware parsing. Similarly, LPBF capability mapping remains dependent on expert knowledge and is not yet fully automated. Ergonomic DSS models based on OWAS, NIOSH and REBA are useful for structured posture assessment, but they do not fully capture individual worker characteristics, psychosocial factors or broader organisational determinants of ergonomic risk [13, 37, 51].

### Discussion to the research questions

The discussion conducted in the article provides a basis for answering the research questions formulated in the study. The integrative research question concerns how modern information processing systems are incorporated into decision-making models in the context of production operations. The reviewed literature indicates that such integration should be understood as a staged socio-technical process rather than as the isolated implementation of a specific digital tool.

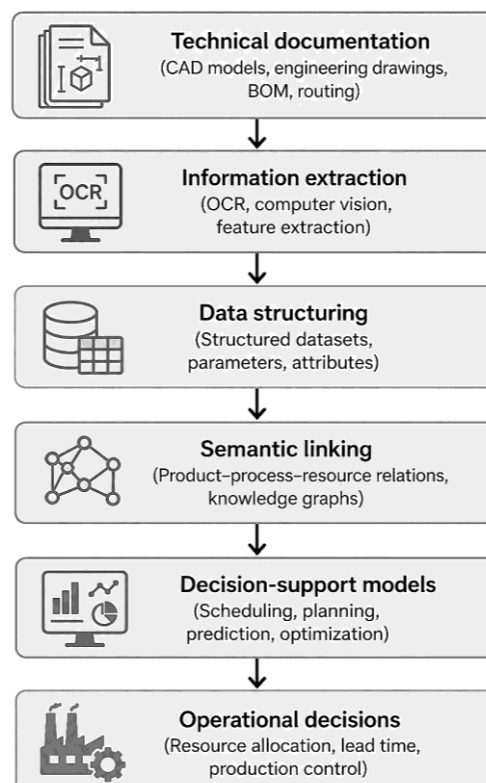
In the first stage, operational problems are reformulated as decision problems by defining the decision context, relevant actors, performance indicators and system boundaries. In the second stage, technical, operational and organisational data are identified, digitised, structured and prepared for analytical use. In the third stage, these data are linked with decision-making models, including mathematical optimisation, multi-criteria decision-making methods, simulation, reinforcement learning, digital twins, ontologies, rule-based extraction procedures and AI-supported classification techniques. In the fourth stage, the results generated by these models are translated into decision-relevant outputs and made accessible to users through dashboards, graphical interfaces, scenario-analysis tools or recommendation systems. Finally, the system is validated, updated and refined on the basis of feedback from real production operations. This perspective shows that integration is not limited to the deployment of ERP systems, OCR tools, digital twins or AI algorithms. Rather, it involves the establishment of a controlled relationship between data sources, information-processing mechanisms, analytical decision models, human decision-makers and operational feedback loops. The effectiveness of this relationship depends on several interrelated conditions. Data maturity determines whether the system can progress from descriptive reporting to predictive or prescriptive decision support. Organisational prerequisites influence whether the system can be accepted, trusted and embedded in daily decision-making routines. Implementation risks define the conditions under which integration may be disrupted or fail. Expected benefits and limitations determine the realistic scope of decision support that can be achieved in production operations. Consequently, the three analysed dimensions – *identification of the stages of information-system implementation*, *organisational prerequisites for the effective adoption of information systems*, and *expected benefits and limitations of information-system-supported decision-making* provide a structured response to the research question. The identification of implementation stages explains how integration should be organised over time. The required data maturity defines the informational conditions necessary for reliable model operation. Organisational prerequisites specify the managerial, technical and social conditions required for effective adoption. Risks indicate the potential points of failure in the integration process. Expected benefits and limitations clarify the practical value and boundaries of information-system-supported decision-making in production operations. Taken together, these dimensions show that the integration of modern information processing systems into decision-making models is a gradual, data-dependent and organisation-dependent process, in which technological capabilities must be aligned with operational needs and managerial decision practices.

## CONCLUSION AND FUTURE RESEARCH

Based on the identified benefits, challenges, technological progress, and implementation determinants of decision models and information processing systems in manufacturing enterprises, the integration of technical information processing systems with decision models can be further specified and analysed. The analysis of 78 articles, it can be concluded that information-processing-related terms are strongly represented in the analysed literature sample. However, their connection with operational decision-making models remains relatively limited. These findings indicate the need for further research on the integration of information tools used for the acquisition, extraction and processing of technical information with decision-support models in manufacturing enterprises.

The combination of technical information processing systems into decision models should be understood as a layered transformation from documentation and operational data into decision knowledge. The reviewed studies indicate that this transformation begins with the extraction and structuring of technical information from engineering drawings, CAD files, title blocks, dimensions, tolerances, GD&T symbols and material descriptions. At this stage, the main objective is to convert human-readable documentation into machine-processable data.

The integration mechanism identified in the literature can be conceptualized as a layered transformation from technical documentation to operational decision-making, as illustrated in Figure 12. The proposed architecture presents the transformation of dispersed technical and operational data into decision-support knowledge within manufacturing environments. The model consists of five sequential layers: technical documentation, information extraction, data structuring, semantic integration, and decision-support models, leading to operational decision-making.



**Fig. 12 Integrated decision-support architecture**

**Alt text:** Flowchart showing how technical documentation is transformed into data-based operational decisions.

The quantitative results reported in the literature confirm that CAD pattern identification layer is technologically advanced. However, the extracted data do not yet constitute decision knowledge. They become decision-relevant only when they are linked with process requirements, quality criteria, resource capabilities and operational constraints.

Studies on digital twins and product–process–resource modelling show that product data can be transformed into process requirements and then matched with available resources. This creates a direct link between engineering information and decisions made in production preparation. In this sense, the technological department can be viewed as an organizational point where technical information is translated into process decisions. However, the reviewed literature also suggests that this translation is still only partly automated. Process planning still depends on expert knowledge, company-specific rules and incomplete system interfaces.

Decision models cannot rely only on technical documentation. They must also include order data, workload, resource availability, machine capacity, workforce capacity and due-date constraints. The reviewed studies on lead time prediction and Masterplan-based planning demonstrate that operational feasibility depends on the relationship between required workload and available capacity. This extends the role of information processing systems from technical data extraction to production decision support. It also shows that a technically feasible product may still be operationally infeasible if capacity, timing or resource constraints are not satisfied.

Process mining and machine learning studies show that event logs can be transformed into process models, remaining-time predictions and bottleneck diagnoses. This indicates that production plans are not static. They change under the influence of machine failures, urgent orders, rework, missing materials, workforce availability and disturbances on the shopfloor. Therefore, an integrated decision model should not end at process planning. It should also include feedback from execution data. Such feedback makes it possible to update decisions during production and not only after the process has been completed.

The reviewed literature also confirms the importance of semantic integration. Knowledge graphs and ontologies provide a mechanism for linking dispersed data sources. They can connect engineering drawings, CAD models, BOMs, routings, process parameters, resources, event logs and analytical models. Their value lies in making relationships explicit. These relationships are essential for decision-making because production decisions are not based on isolated data points. They depend on relations between product characteristics, process requirements, resource capabilities, capacity constraints, quality criteria and actual process execution.

Despite this progress, the integration remains incomplete. Drawing-processing studies achieve measurable results in data extraction, but they rarely continue toward full operational decision-making. Digital-twin and process-planning studies provide strong conceptual architectures, but they often remain dependent on simplified use cases, manual knowledge input or limited industrial validation. Knowledge graph studies provide semantic infrastructure, but they do not always demonstrate direct decision outcomes in production practice.

The main research gap therefore concerns the limited number of coherent models that connect engineering documentation, process planning, resource capability, capacity assessment and execution data into one decision-support structure for production operations. Future research should not focus only on improving individual algorithms for data extraction, prediction or optimization. It should also address the architecture of integration between these layers.

In particular, there is a need for models that can transform technical information from documentation into process requirements, link these requirements with resources and capacity, and update decisions using real execution data from production systems.

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