

Review

Mixed-model and multi-model assembly lines: A systematic literature review on resource management

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ABSTRACT

In modern dynamic manufacturing context, product personalisation, and the production-line customisation it may require, are crucial sources of competitiveness, making mixed-model and multi-model assembly lines indispensable. The variability resulting from both internal and external factors, along with resource flexibility, plays a critical role in these settings. Nonetheless, systematic analyses of how resources are considered in such environments remain limited, particularly about variability and the interactions among different resource types. Thus, this work conducts a Systematic Literature Review, analysing 63 studies on Mixed-Model Assembly Lines (MMALPs) and Multi-Model Assembly Lines (MuMALPs). The review investigates resource characteristics – such as space, operator skills, costs, or equipment availability – and whether and how variability in operating times or market demand is addressed. The review shows that cost and availability are the most frequently examined resource characteristics, while space remains comparatively underexplored. Line design and line balancing stand out as the primary objectives, typically tackled via integer programming or metaheuristics, whereas machine learning – though less common overall – is more often employed under high-variability conditions. The results offer practical insights for both researchers and practitioners by highlighting the current gaps uncovered by these findings and suggesting avenues that would be particularly valuable to explore in light of the results obtained, thereby underscoring the need for more in-depth research on flexible and reconfigurable lines, as well as broader implementation in real-world applications in MMALPs and MuMALPs.

1. Introduction

The increasing complexity of industrial processes and the inevitable evolution towards more customized and flexible production systems make the adoption of advanced solutions for the management and optimization of assembly lines crucial. According to McKinsey's report "The value of getting personalization right – or wrong – is multiplying" [1], 71 % of consumers expect personalized interactions from companies, and firms excelling in personalization earn 40 % more revenue from these activities compared to the average; the same report also estimates that enhancing personalization capabilities could generate over US\$1 trillion in additional value across various sectors in the United States. These data underscore that personalization not only meets consumer expectations but also offers a significant competitive advantage.

While the market figures above concern product personalisation – tailoring features for each individual customer – manufacturers usually answer through production-line customisation, i.e., reconfiguring resources so one line can flexibly assemble multiple variants. The two concepts, although related, are distinct, for instance technologies such as additive manufacturing now allow high personalisation without a fully customised line [2].

The former aspects have also led to the development of increasingly complex production lines, including Mixed-Model Assembly Lines (MMALs) and Multi-Model Assembly Lines (MuMALs). MMALs and MuMALs are two organizational strategies for managing product variety in manufacturing. MMALs assemble different models from the same product family in an intermixed sequence on a single line, without significant setup times. This enables high flexibility and continuous flow,

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making them ideal for environments with frequent model changes [3]. In contrast, MuMALS produce different models in separate batches on the same line, with potential setup times between batches. While less flexible, this approach simplifies scheduling and may be more suitable when model changes are costly or require specific adjustments [4].

Moreover, the current market is characterized by increasingly shorter product life cycles and rapid shifts in trends that make long-term forecasting a challenge. This volatility concerns the Product Life Cycle (PLC). By contrast, the manufacturing system follows its own Production Life Cycle (PrLC) – design, ramp-up, operation, reconfiguration and retirement – which dictates investments in flexible resources and reconfigurability [5]. This unpredictability first affects market demand, compelling companies to cope with fluctuating requirements, and then impacts the production system, which must handle numerous different models featuring variable operating times. Recent studies stress the need to integrate reconfigurability, product diversity, and demand uncertainty into mixed- or multi-product assembly line environments, emphasizing that overlooking task reassignments, NP-hard balancing challenges, or uncertain parameters can undermine operational efficiency [6–8]. A recent BCG analysis, titled “Boosting Resilience with Production as a Service” [9] confirms this trend, indicating that manufacturers require a new value proposition to meet the heightened demand for highly customized products, particularly from younger consumers. According to the same study, 77 % of surveyed companies plan to design their next production facility with a focus on flexibility, whereas only 23 % aim to prioritize operational efficiency for the lowest possible cost. Nevertheless, cost management remains a critical concern, especially given rising inflation in Europe and the United States.

In a separate report of BCG: “The Automation Revolution in Manufacturing” [10], underscores how such market-driven variability creates tangible implications for both assembly processes and supporting equipment. Tasks involving complex component geometries, flexible materials, or numerous product variants often exceed the capacity of conventional automation. By integrating advanced sensors, computer vision, and machine learning models into production systems, manufacturers can enable machinery to adapt autonomously to diverse operational conditions. This capability enables companies to significantly reduce conversion costs, up to 25 % in one documented case. Together, these insights demonstrate that relying solely on standardized, static production lines is no longer sufficient. Instead, reconfigurable and flexible assembly lines, frequently implemented in mixed-model or multi-model configurations, are indispensable for swiftly responding to continual market shifts while maintaining stringent cost control. Industry 4.0 technologies enable scalable uniqueness, and Industry 5.0 blends technology and humans for greater levels of sustainability. While Industry 4.0 offers enabling technologies for mass personalization, Industry 5.0 demands mass personalization by further collaboration between humans, machines, and digital technologies for resilience and sustainability [11].

Given the importance of these configurations in the global industrial landscape, many researchers have focused on MMALs and MuMALS. For example, a matrix method supported by a genetic algorithm can reduce cycle time (from 344 to 336 s) during a remanufacturing phase, effectively managing variability and improving production pace [12]. Additionally, the use of machine learning algorithms such as XGBoost has achieved a 161 % performance increase through online learning techniques compared to traditional offline solutions [13]. Still within the realm of machine learning, reinforcement learning algorithms like Q-Learning have optimized assembly sequences in 98.3 % of analysed cases, highlighting significant efficiency gains [14]. Finally, dynamic task assignment models have enabled companies to reduce the number of required operators, thereby lowering costs while maintaining high efficiency standards [15].

1.1. Literature gap and novelty of the present work

The literature on managing and optimizing MMALs and MuMALS is extensive and it is testified by the presence of four literature review [16–19]. A common theme emerging from these contributions is the need to address challenges arising from high product variety, product personalisation, and limited resources in today’s competitive market.

The review by [19] offers a comprehensive overview of decomposition methodologies for scheduling problems in manufacturing systems. The former study categorizes various strategies – from high-volume, low-variability lines to low-volume, high-variability ones – with a focus on balancing and sequencing issues in mixed-model and multi-model configurations. It examines techniques such as genetic algorithms, simulated annealing, and ant colony methods, and identifies gaps that call for multi-objective approaches and the integration of advanced methodologies.

Similarly, the systematic review by [18] underscores the growing importance of soft computing methods – including Genetic Algorithms, Simulated Annealing, and Ant Colony Optimization – to reduce workstation numbers, balance workloads, and optimize cycle times. This review also highlights emerging concerns like sustainability and human factors, reflecting the broader shift toward more responsible production strategies.

[16] further contribute by analysing workforce planning and assignment in mixed-model assembly lines, emphasizing the potential of integrating reconfigurable manufacturing systems with workforce reconfiguration strategies to enhance operational flexibility.

Finally, [17] provide insights into productivity forecasting in complex production contexts, demonstrating that advanced machine learning approaches are particularly effective in handling the high variability typical of highly customized environments.

Collectively, these studies form a cohesive framework that leverages technological and methodological advancements to improve efficiency, flexibility, and responsiveness in modern assembly lines. However, none of the four review studies delves into which aspects of resource management receive the most attention in mixed-model assembly line problems (MMALPs) and multi-model assembly line problems (MuMALPs). While these studies provide a detailed analysis of various methods, they do not specifically focus on resource management aspects. In particular, they don’t investigate which resource characteristics are emphasized, how these characteristics are handled, which methods or combinations are predominantly applied to them, and what specific objectives are pursued from a resource-centred perspective. Nor do these works analyse the relationships between resource characteristics, study goals, and the methodologies applied. Furthermore, none of them explores how variability is addressed in these contexts, what types of variability are examined (e.g., demand variability), and which approaches are most commonly adopted to manage them. Consequently, this systematic review aims to fill these gaps by examining not only resource management in terms of the characteristics studied and how, but also the treatment of variability in MMALs and MuMALs.

1.2. Research questions and contributions

The present study seeks to explore the role of equipment, tools, and machinery, considering them as limited and strategic resources, essential not only for the design, balancing, and sequencing of assembly lines but also for effectively managing the complexity and high variability of MMALs and MuMALs. Moreover, this analysis becomes critically important when resources are associated with high costs and long procurement times. In such contexts, proper balancing and optimal allocation of equipment can provide a significant competitive advantage, reducing bottlenecks and improving the overall efficiency of the entire production system.

Based on the former consideration and the highlighted gaps, the present study aims to answer the following research questions (RQs):

- **RQ1:** in MMALPs and MuMALPs, how are resources regarded as critical and strategic elements, and which resource characteristics are taken into account?
- **RQ2:** what types of variability are considered when specific resource characteristics in MMALPs and MuMALPs are examined?
- **RQ3:** what combinations of objectives and methods are predominantly used when investigating specific resource characteristics in MMALPs and MuMALPs?

This study makes several important contributions to the field of resource management in MMALPs and MuMALPs. First, it aims to identify which resource characteristics are the least explored to date by introducing a clear classification framework that organizes these characteristics into five macro categories: Space, Availability, Costs, Performance, and People. In doing so, the work contributes to the literature by demonstrating that, although costs and availability are extensively studied, aspects such as space and people factors remain less explored, thereby underlining the strategic importance of these neglected areas.

Furthermore, the study seeks to investigate how variability – defined in terms of fluctuations in operational times and market demand – is considered within the predominant combinations of research objectives and methods applied to each resource characteristic. This systematic mapping not only clarifies existing practices but also identifies gaps, offering a structured basis for future research.

An additional contribution is provided by the analysis of research objectives – which include design, balancing, feeding, sequencing, and performance analysis – and their correlation with the most frequently employed methodological approaches when considering a specific resource characteristic. In this way, the study highlights the prevalent combinations of objectives and methods for each resource characteristic, while also pinpointing the less-studied areas, thus offering valuable insights for the development of more effective strategies in complex industrial settings.

Finally, this work provides practical guidelines for future developments, indicating promising directions for researchers seeking to extend these strategies and address new challenges in increasingly complex production environments.

The structure of the work is as follows:

Section 2 describes the review methodology, based on the PRISMA framework, and defines the criteria for literature selection, with a focus on critical resource management and operational variability in production contexts. **Section 3** presents the state of the art, analysing the publications to identify major research trends and areas of interest, supported by an analysis of Author Keywords to highlight sector evolution. **Section 4** examines how resource characteristics are addressed in MMALs and MuMALs, highlighting the main groups of attributes considered within these problems. **Section 5** examines how variability is factored into these contexts. It highlights which combinations of resource attributes and variability receive the most attention and identifies less-explored areas. **Section 6** examines commonly addressed objectives (e.g., design, balancing, sequencing, etc.) and solution methods (e.g., integer programming, metaheuristics, machine learning, etc.), highlighting frequent objective-method combinations, the role of variability, and a growing trend toward integrated, multidisciplinary approaches. **Section 7** thoroughly discusses the main limits in resource management for mixed- and multi-model assembly lines. It then presents a framework of five thematic areas, grouping future developments to offer clear research guidance and bridge theory-practice gaps. In closing, **Section 8** concludes the work by synthesizing the main findings and contributions, discussing both the theoretical and practical implications of the analysis, and outlining the limitations and future research directions necessary to advance resource management in MMALs and MuMALs.

2. Methodology: PRISMA-based systematic review

The systematic literature search started in October 2024. At the onset of the review process, the identification of relevant keywords was carried out through focus groups and iterative trials, enabling the researchers to pinpoint coherent studies and define new keywords tailored to the specific focus on mixed-model and multi-model assembly lines. The subsequent review was conducted using a systematic approach based on the PRISMA framework to ensure rigor, transparency, and replicability. In the Identification Phase, comprehensive database searches were performed with the defined keywords to gather all potential studies addressing the optimization of multi-model and mixed-model assembly lines, with particular attention to the management of equipment, tools, and machinery as limited resources, as well as the integration of stochastic behaviours such as demand variability and variability in task execution times by operators. During the Screening Phase, titles and abstracts were examined to quickly exclude irrelevant studies, and in the Eligibility Phase, full texts were assessed against specific criteria. The final set of included articles formed the corpus for the review, grounding the study in a robust and focused body of literature.

To clarify the boundaries of the search, **Table 1** summarises the methodological scope adopted for this systematic review, namely the information sources, document types, language restrictions, temporal window and disciplinary areas considered.

2.1. Search strategy

This subsection outlines the four PRISMA phases adopted in the review. We first identified records in Scopus with a progressively refined search string; we then screened titles and abstracts, assessed full texts against pre-defined criteria, and finally retained 63 studies for synthesis. Details of each phase follow.

Identification phase

The preliminary search was conducted using the Scopus database, recognized for its extensive coverage of high-quality scientific publications. The construction of the search string followed a structured and progressive logic, designed to gradually narrow the research domain and obtain highly relevant results for the study topic. This approach enabled a transition from a broad view of the industrial context to a specific focus on equipment used in assembly lines.

The starting point was defining a broad context, including all industrial manufacturing settings, particularly those operating on assembly lines. During this phase, generic terms were used to ensure that no potentially relevant contributions were excluded. Therefore, to describe this production context we chose the following string:

Subsequently, the focus narrowed to companies adopting mixed-model or multi-model production logic. This category includes industries producing multiple models with aesthetic and functional variations, a crucial element for our research scope. With regard to describing the assembly-line production strategy, the following string was used:

The search was further refined to include only studies addressing key business challenges related to optimization, balancing, and resource

Table 1
Methodological scope of the systematic literature review.

Aspect	Specification
Databases searched	Scopus
Document Type	Peer-reviewed journal articles and conference papers
Language	English
Time Window	2014–2024
Subject Areas	Engineering, Computer Science, Decision Sciences, Mathematics, Economics, Econometrics and Finance, Business, Management and Accounting

("manufacturing line*" OR "industr* line*" OR "production* line*" OR "production - line*" OR "production-line*" OR "assembl* line*" OR "assembly - line*" OR "assembly-line*")

("multi product*" OR "multi-product*" OR "multi - product*" OR "mix* product*" OR "mix*product*" OR "mix - product*" OR "mixed - product*" OR "multi model*" OR "multi-model*" OR "multi - model*" OR "mix* model*" OR "mix*model*" OR "mix - model*" OR "mixed - model*" OR "multi item*" OR "multi-item*" OR "multi - item*" OR "mix* item*" OR "mix*item*" OR "mix - item*" OR "mixed - item*")

sizing, which represent the core issues companies face in complex production environments. Keyword selection was therefore oriented towards terms clearly indicating these study objectives:

Ultimately, the search scope was further narrowed to focus specifically on the concept of resources, defined as machinery, tools, and equipment used by operators. This level was essential to select articles addressing not only resource management in a broad sense but also considering these resources as key elements central to the analysed problem. Therefore, the following string was chosen for the specific research focus:

("tool*" OR "resource*" OR "asset*" OR "equipment")

This logic, structured around concentric domains and organized using logical operators AND and OR, enabled the construction of an articulated and effective search string. The asterisk ("*") broadens the search by matching partial words, ensuring we capture relevant studies even if terms have minor spelling variations or endings, with the full search string summarised in Fig. 1. As a result, the initial search identified a corpus of 285 articles.

2.2. Inclusion and exclusion criteria

To refine the corpus identified in Section 2.1, two sequential PRISMA steps, screening and eligibility, were applied according to the rules detailed below, in order to determine the final set of Included Articles.

Screening phase

To ensure that the results were strictly relevant, inclusion and exclusion criteria were applied. Only articles published in English and belonging to specific disciplinary fields – including engineering, computer science, decision sciences, mathematics, economics, and business management – were considered. Additionally, a ten-year time frame (2014 – 2024) was selected to ensure a sufficiently large corpus for meaningful analysis and to capture year-by-year trends in the evolution of research on mixed- and multi-model assembly lines.

This screening phase led to the exclusion of 127 articles, reducing the sample to 158 articles.

Eligibility phase

The next step involved a further filtering of the selected articles. In this phase, the selected articles underwent further filtering, which was independently conducted by two authors to ensure rigor. A total of 35 articles were eliminated for various reasons: 11 were conference proceedings, 21 were inaccessible due to restrictions or lack of licenses, and 3 were excluded for other reasons, such as being withdrawn or not meeting the language criteria. As a result, the number of eligible articles

LEVEL	KEYWORDS	PURPOSE
Production Context	("manufacturing line*" OR "industr* line*" OR "production* line*" OR "production - line*" OR "production-line*" OR "assembl* line*" OR "assembly - line*" OR "assembly-line*") AND	Covers generic manufacturing and assembly-line settings.
Assembly Line Production Strategy	("multi product*" OR "multi-product*" OR "multi - product*" OR "mix* product*" OR "mix*product*" OR "mix - product*" OR "mixed - product*" OR "multi model*" OR "multi-model*" OR "multi - model*" OR "mix* model*" OR "mix*model*" OR "mix - model*" OR "mixed - model*" OR "multi item*" OR "multi-item*" OR "multi - item*" OR "mix* item*" OR "mix*item*" OR "mix - item*" OR "mixed - item*") AND	Targets firms using mixed- or multi-model production.
Study Objective	("optimi*" OR "level*" OR "management" OR "siz*" OR "allocat*" OR "balanc*" OR "contingenc*" OR "conflict*" OR "contention*" OR "competition*" OR "request*") AND	Seeks studies on optimization, balancing, and resource sizing.
Resource Focus	("tool*" OR "resource*" OR "asset*" OR "equipment*")	Focuses on machinery, tools, and operator equipment as key resources.

Fig. 1. Search-string design for the systematic review. The left column lists the four hierarchical levels used to structure the query, the centre column shows the exact keywords and Boolean operators combined at each level, and the right column states the intended scope or rationale ("Purpose") of the corresponding keyword group.

was reduced to 123.

Included articles

The selected articles were thoroughly reviewed by evaluating their title, abstract, methodology, and conclusions to verify whether they effectively addressed the topic of assembly lines, with a particular focus on considering resources as a key element of the study. This analysis led to the identification of several studies that were not fully relevant. The main reasons for exclusion were:

- *Off-topic*: 8 articles showed no connection to assembly lines despite the various filters applied.
- *Not relevant*: 24 articles, although covering related topics, did not meet fundamental criteria. Specifically, they did not address mixed-model or multi-product environments, thus falling outside the classification of General Assembly Line Problems (GALP) and instead belonging to Simple Assembly Line Problems (SALP) (e.g., a single-

("optimi*" OR "level*" OR "management" OR "siz*" OR "allocat*" OR "balanc*" OR "contingenc*" OR "conflict*" OR "contention*" OR "competition*" OR "request*")

model line-balancing algorithm for one product variant under fixed demand).

- *Different focus*: 28 articles, despite falling within the GALP classification, did not analyse resources as a key element of the problem. Instead, they focused on other aspects, oversimplifying resource behaviour in their models (e.g., a sequencing study on a fixed-demand, single-machine system that minimises setup-change frequency while presuming unlimited labour, no tool constraints, and zero probability of machine downtime).

At the end of the review, 63 articles fully met the inclusion criteria and form the solid foundation for the study of mixed-model and/or multi-model assembly lines, with a specific focus on resource management. To summarise the step-by-step procedure outlined above, Fig. 2 presents the PRISMA flow diagram, showing the operational path followed and the results obtained at each phase.

2.3. Data extraction and synthesis

After importing the bibliographic records in.csv format, we compiled a master spreadsheet in Microsoft Excel. An iterative coding process was followed: each time a relevant attribute emerged during full-text reading, a new column was appended to the sheet, resulting in a structured codebook of binary variables (yes/no flags for the presence of a given feature) plus descriptive fields (e.g., optimisation algorithm, noteworthy remarks). This table served two purposes:

1. Preliminary screening: Excel filters enabled rapid, ad-hoc queries (e.g., “papers using genetic algorithms and modelling tool availability”) and provided immediate frequency counts for each attribute.
2. In-depth exploration: The spreadsheet was exported to Python for quantitative synthesis. Correlation matrices and cross-tabulations revealed associations between line type, resource category and optimisation technique. Simple scripts were used to visualise interaction patterns.

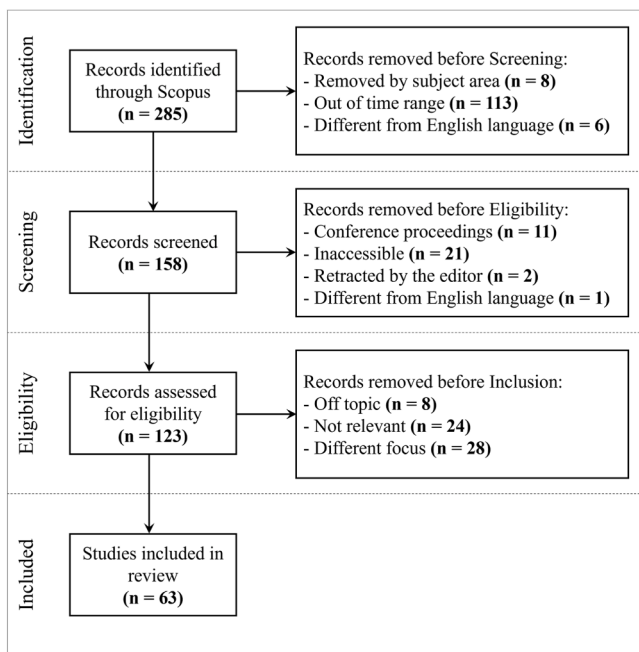


Fig. 2. PRISMA flowchart illustrating the systematic review process. It shows the steps from the identification of records through Scopus ($n = 285$) to the final inclusion of studies ($n = 63$), with records removed at each stage based on specific criteria.

3. Quantitative results: Publication analysis and research trends

The analysis of publications from 2014 to 2024 highlights a total of 41 articles published in journals, 21 contributions presented at international conferences, and one book. Among the sectors analysed, the automotive industry emerges as the most extensively studied and stands out as the primary focus of research. Significant attention is also given to the electronics and fashion sectors. Additionally, industries such as aerospace, naval, furnishings, and agri-food are included in the analysis, reflecting a degree of diversification in research interests within the assembly line domain. As shown in Fig. 3, the graph reports the yearly publication count, with 2022 representing the peak in the dataset. The year 2021 is not displayed because no relevant papers were retrieved; omitting this zero-value point preserves space and improves the visual clarity of the figure.

The leading outlets in the dataset are *International Journal of Production Research* (7 papers), *Computers & Industrial Engineering* (4), and *Journal of Manufacturing Systems* (3), while each of the remaining journals plotted contributes two papers; all other sources yield only a single publication and are omitted for clarity, as summarised in Fig. 4. Conferences represent an important platform for disseminating early-stage research, with a total of 21 publications. Among the most frequent conferences are “IFAC-PapersOnLine”, “Procedia CIRP”, and “IOP Conference Series: Materials Science and Engineering”, confirming the focus on topics such as automation and advanced manufacturing.

To identify key research trends and emerging areas of interest, an Author-Keywords analysis was carried out on the final corpus of papers retained after the PRISMA screening and covering the time span 2014 – 2024. Fig. 5 displays the resulting frequency chart, where individual terms were consolidated into higher-level categories to avoid splitting semantically equivalent keywords and thus misrepresenting their actual incidence.

The plot reveals a pronounced emphasis on “Mixed Model Assembly Processes” “Product Variability” and “Assembly Line Balancing/Design Problems” confirming that research is largely driven by the challenges of balancing, scheduling, and resource allocation in high-variety production environments. Strong occurrences of “Manufacturing Systems and Processes”, “Planning and Scheduling” and “Flexibility” further underscore the need for modern, adaptable lines capable of rapid model changeovers.

Notably, the presence of “Ergonomics and Human-Robot Collaboration”, “Workforce Management” and other related keywords signals a growing human-centric perspective, while topics such as “Robust Optimization and Control” point to an emerging interest in the resilience of production systems. Finally, the prominence of “Logistics and Equipment” highlights the persistent importance of material flow and tooling decisions in boosting overall system efficiency.

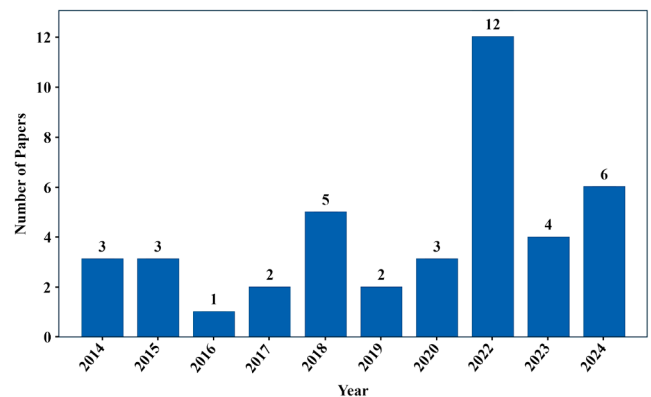


Fig. 3. Annual distribution of the papers considered in the review (2014 – 2024). The x-axis lists the publication year, and the bars (left y-axis, “Number of Papers”) show how many articles appeared in each year.

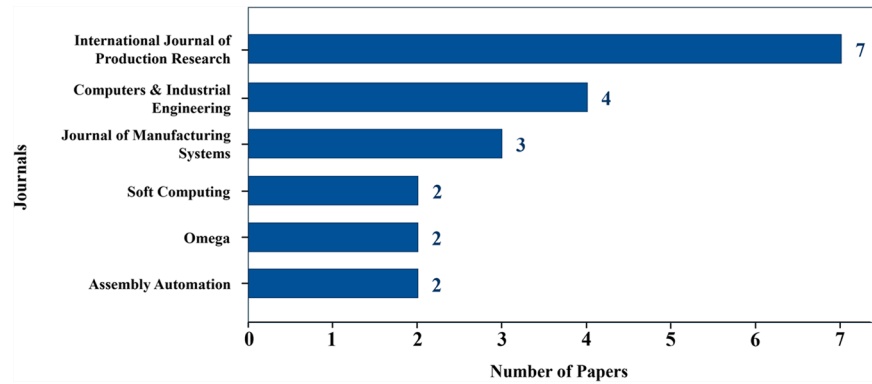


Fig. 4. Horizontal bar chart of publication volume by journal (2014 – 2024). The y-axis lists the journal titles, while the x-axis reports the corresponding number of papers retrieved within the 2014–2024 time window. The three most prolific outlets are International Journal of Production Research (7 papers), Computers & Industrial Engineering (4 papers), and Journal of Manufacturing Systems (3 papers).

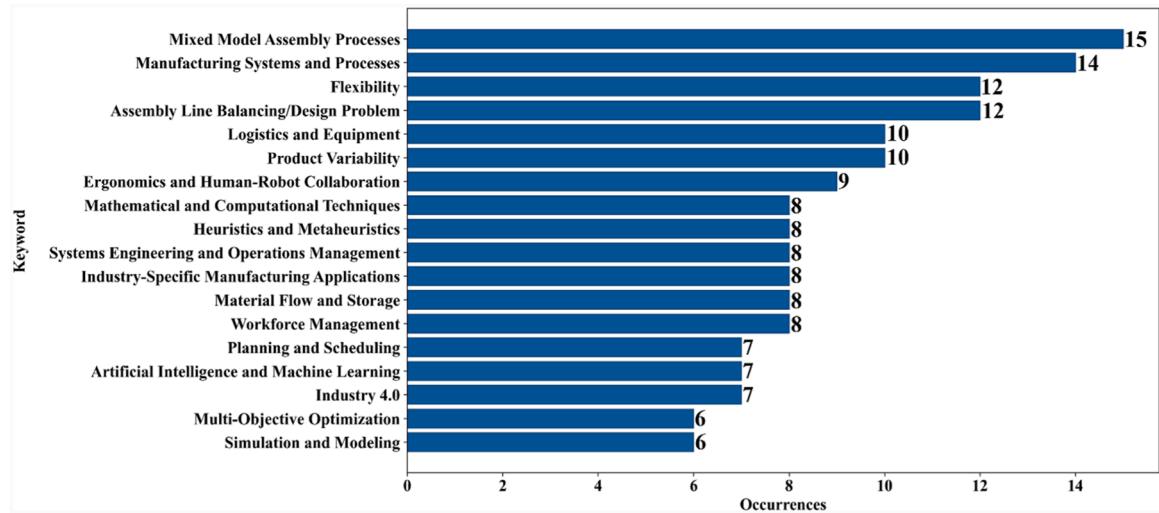


Fig. 5. Horizontal bar chart of the consolidated author-keyword categories extracted from the articles retained after the PRISMA screening (publication years 2014–2024). The y-axis lists the categories, while the x-axis reports their frequency; bars are ordered by decreasing number of occurrences.

4. Resources characteristics analysis

This chapter aims to address RQ1. Specifically, In [Section 4.1](#), the work analyses the key resource characteristics examined in the literature, organizing them into five main categories – Space, Availability, Costs, Performance, and People – and delving into the primary aspects addressed for each characteristic. Meanwhile, [Section 4.2](#) investigates the components of variability in production environments, categorizing it into time variability, demand variability, and a combination of both, and then explores how variability is considered for each of the resource characteristics identified in [Section 4.1](#).

The main characteristics addressed in the 59 articles dedicated to resource management were identified, leading to the classification of five macro-groups: Space, Availability, Cost, Performance, and People. The Space group encompasses all aspects related to the available area and the footprint occupied by equipment, machinery, and personnel along the production line. The Availability group focuses on the proper sizing of resources according to the tasks to be performed, considering the possibility of sharing equipment, machinery, or multi-skilled operators. The Cost group includes economic aspects, analysing resource costs and their impact on problem-solving. The Performance group considers studies that propose key performance indicators (KPIs) specifically designed to measure aspects directly related to resources, such as resource utilization, resource ergonomics, and resource flexibility.

Finally, the People group concentrates on characteristics related to ergonomics and human factor management, including workload, stress, mental fatigue, experience, and learning capabilities.

A preliminary high-level analysis, as illustrated in [Fig. 6\(a\)](#), reveals that when addressing resource management in Mixed Model and Multi Model problems, the most frequently analysed characteristics predominantly belong to the Cost group. The Availability group is also frequently investigated, showing a notable gap compared to the other characteristic groups. Conversely, characteristics such as the Space occupied by resources appear to be the least explored in this context. Within these characteristic groups, it is possible to identify the most commonly addressed elements in mixed-model and multi-model resource management, as summarized in [Fig. 6](#).

It is important to note that the values shown in histograms can exceed the total number of articles analysed, since several studies face more than one characteristic of the resources simultaneously.

4.1. Classification of resource space

The Space group can be divided into two mutually exclusive categories, as illustrated in [Fig. 6\(b\)](#). Specifically, some studies treat space solely as an operational constraint, while others consider it exclusively as a cost factor:

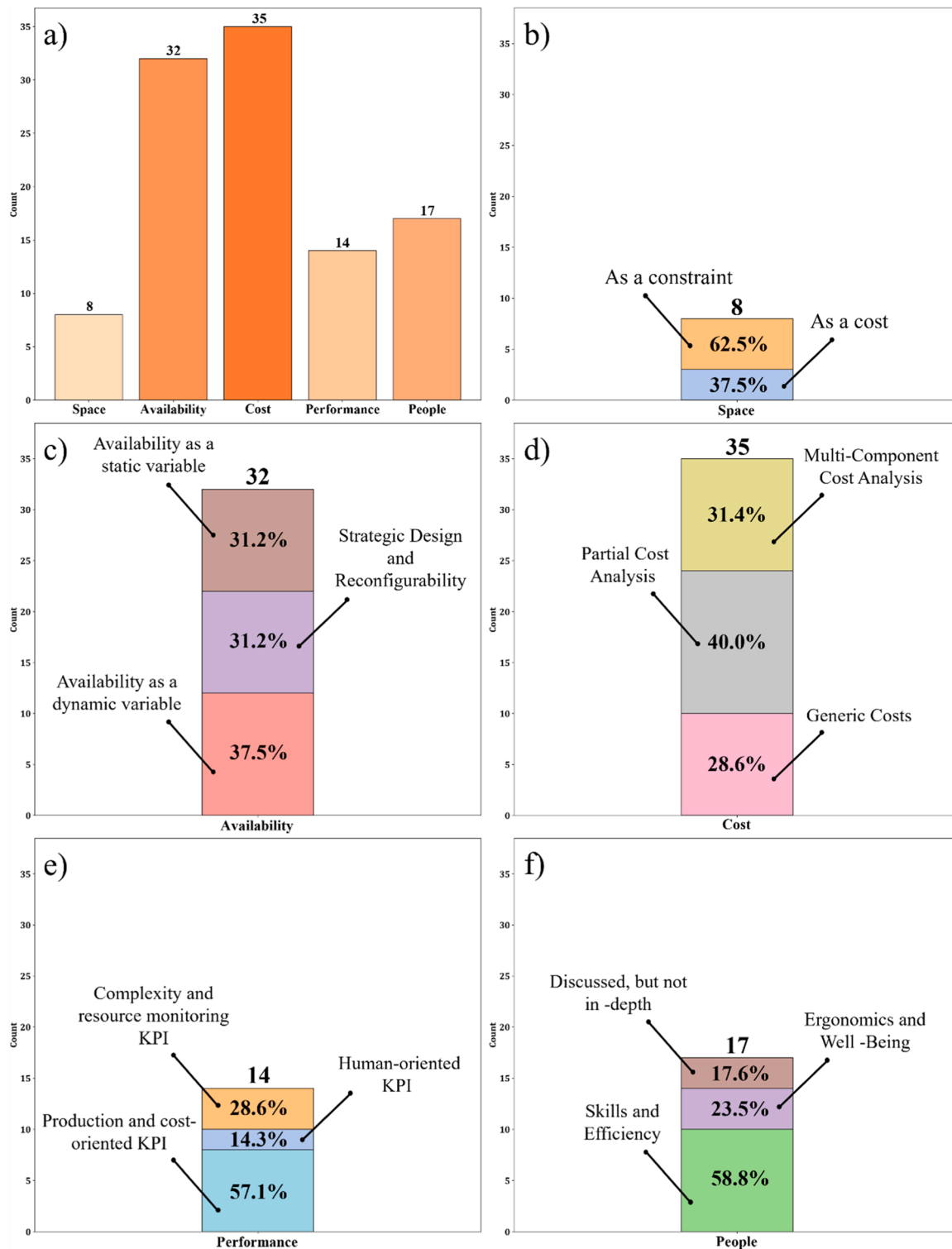


Fig. 6. (a) The histogram illustrates the number of articles addressing a specific characteristic. (b) Breakdown of the Space group. (c) Breakdown of the Availability group. (d) Breakdown of the Cost group. (e) Breakdown of the Performance group. (f) Breakdown of the People group.

– *Space is treated as a constraint*: articles analyse available space as a key factor in feasibility and physical configuration. Examples include the need to ensure a sufficient number of stations, buffers, or storage areas to accommodate materials and equipment, or the requirement to comply with specific dimensional constraints when installing machinery. In these studies, space plays a role comparable to other operational constraints, such as cycle times or workforce skills, directly influencing line configuration and imposing strict limitations on resource allocation [20–24].

– *Space is treated as a cost*: its physical dimension is associated with financial parameters, such as rental or acquisition costs of production areas, storage management and maintenance costs, and even opportunity costs related to suboptimal layout usage. In this perspective, spatial constraints lose their purely logistical and organizational nature, becoming an economic variable where optimization aims to minimize or balance investment in space. This involves evaluating alternative design solutions or layout choices that offer

more advantageous trade-offs in terms of total management costs [25–27].

4.2. Classification of resource availability

The availability of resources can be analysed from different perspectives, depending on the objectives and challenges addressed in the reviewed studies, as illustrated in Fig. 6(c). These perspectives fall into three mutually exclusive categories:

- *Availability as a dynamic variable*: in this research stream, the availability of resources – such as machines, operators, or equipment – fluctuates due to scheduled breaks, tool changes, setups, failures, or other operational uncertainties. For instance, studies in this category focus on scheduling strategies to assign and sequence tasks while accounting for time-dependent resource variations. The main challenge lies in dynamically managing resource allocation and processing times [13,24,28–37].
- *Availability as a static variable*: in these studies, resource availability is treated as a more static constraint that must be managed when distributing tasks among workstations. The focus is on how the inherent limitations of resources – such as operator skills, specialized equipment, or ergonomic factors – affect task allocation. Here, availability serves as an additional constraint to optimize cycle time, the number of stations, and overall resource allocation and utilization [21–23,38–43].
- *Availability as a design and reconfigurability factor*: this perspective is centred on the initial planning of the production system, including decisions on machinery acquisition and automation levels. In these contributions, resource availability is closely linked to the ability to adapt production lines to new requirements, product variations, or demand fluctuations. The studies in this category analyse reconfigurable systems and solutions that enable quick layout adjustments or production setups while minimizing reconfiguration costs and time. The primary objective is to sustain high productivity even in highly variable scenarios, ensuring maximum resource utilization [15,20,44–51].

4.3. Classification of resource costs

In the Cost group, the classification is based on the level of detail adopted in cost analysis, as illustrated in Fig. 6(d). Three distinct categories have been identified.

- *Generic costs*: where studies mention cost as a general factor without developing a detailed analytical model. These contributions acknowledge the economic dimension but do not engage in a quantitative evaluation or formalized cost structure [30,51–59].
- *Partial cost analysis*: focusing on one or a limited set of economic aspects, such as labour or equipment costs. While these studies provide a more in-depth investigation of specific cost components, they do not extend the analysis to the entire cost structure of production [13,15,23,25,34,39,43,45,50,60–64].
- *Multi-component cost analysis*: encompassing studies that integrate multiple cost factors, often within a multi-objective framework. These contributions develop analytical models that consider various cost dimensions simultaneously, providing a comprehensive perspective on economic trade-offs and resource allocation decisions [20,26,27,44,46–48,65–68].

4.4. Classification of resource performance

The Performance group can be divided into three main categories based on the type of Key Performance Indicators (KPIs) analysed, as illustrated in Fig. 6(e).

- *Production- and cost-oriented indicators*: where studies explicitly define KPIs focused on production performance (PrLC viewpoint), such as cycle time and throughput, in combination with economic indicators related to investment and operational costs. These contributions typically address line balancing problems, resource-constrained planning, and economic optimization in multi-product or mixed-model production environments [12,43,59,63,68–71]. Life-cycle costing of the line (equipment acquisition, retrofit, end-of-life) therefore complements the LCA of the product itself, linking PrLC decisions to sustainability [72].
- *Human-oriented indicators*: emphasizing worker safety and well-being. These studies integrate specific KPIs for assessing ergonomic risk – such as the OCRA index and ergonomic risk scores – alongside workload evaluation and labour costs. By combining these human-centric indicators, research in this category highlights how optimizing ergonomics and worker health can coexist with operational efficiency [22,67].
- *Complexity and resource monitoring indicators*: examining specialized KPIs related to system complexity, resource utilization, and real-time monitoring. These studies analyse measures such as structural and dynamic complexity – often quantified through entropy – along with performance tracking of production systems and energy consumption over time. Leveraging advanced analytical techniques, including data mining and machine learning, these contributions demonstrate how detailed monitoring and complexity evaluation provide crucial insights into the robustness, resilience, and sustainability of assembly lines [53,73–75].

4.5. Classification of ergonomics and human factors

Finally, the People group can be divided into three main categories, as illustrated in Fig. 6(f). These categories reflect the different aspects analysed, ranging from skill levels to ergonomics and studies that address the topic in a less detailed manner.

- *Skills and efficiency*: encompassing studies where the human operator is the primary variable in optimization models. These contributions consider both operator skills and efficiency – such as specialization and varying proficiency in performing specific tasks – as well as economic and planning aspects, including labour costs, error-related costs, setup times, kitting, and feeding operations. The objective is to design and manage the production line in a way that maximizes productivity while minimizing waste or overloads, integrating workforce performance and constraints into the model. Unlike studies focusing on ergonomics or system scheduling flexibility, this research directly targets human work optimization, from task allocation based on individual operator skills to cost quantification of manual activities, ensuring a balanced production process [15,26,27,31,40–43,63].
- *Ergonomics and operator well-being*: with studies primarily focusing on integrating ergonomic and well-being metrics – such as the OCRA index, noise exposure, ergonomic load balance, and energy expenditure – with traditional line-balancing objectives, such as cycle time reduction and productivity improvement. In these studies, worker health and safety are essential constraints in the design or restructuring phase of the production line [21,22,55,67].
- *Marginal or indirect reference to the human role*: in this case, the human factor is acknowledged but treated as secondary or indirectly considered during the application of design, balancing, or scheduling methodologies. These studies primarily focus on the structure and architecture of the production process, integrating human operators in a general manner rather than conducting a detailed analysis of skills, costs, or health-related aspects [12,32,49].

Expanding the analysis of resource-related aspects in these contexts reveals how different characteristic groups tend to combine within the

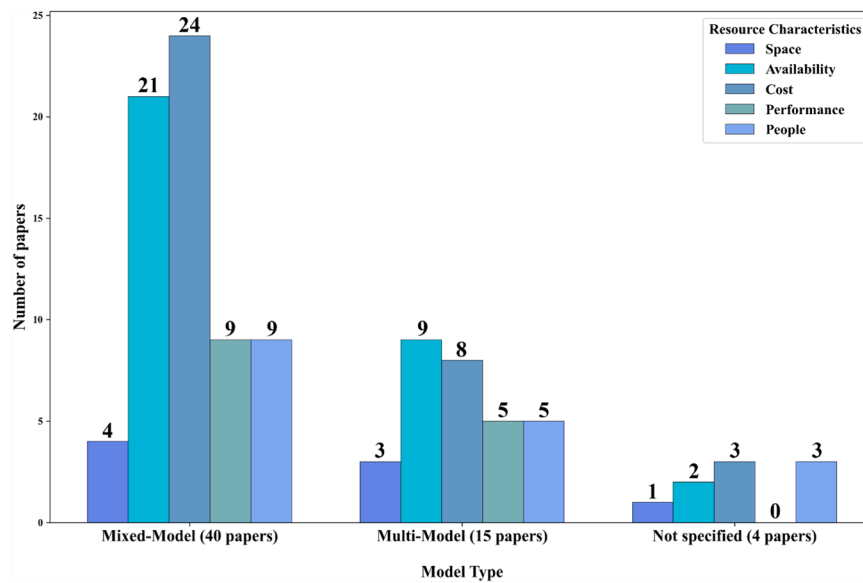


Fig. 8. Pie charts showing, for each line type “Mixed-Model” (40 papers), “Multi-Model” (15 papers) and “Not specified” (4 papers), the percentage of reviewed studies that address each resource-characteristic category (Space, Availability, Cost, Performance, People).

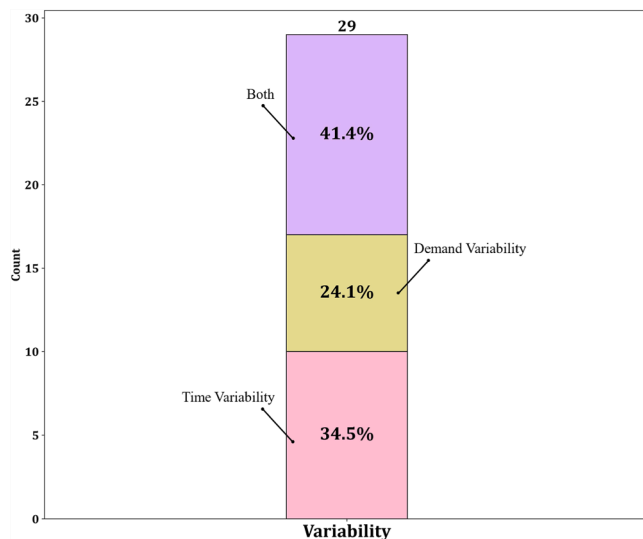


Fig. 9. Histogram of variability analysis of operating times, demand and both factors.

complex challenge in Mixed Model and Multi Model environments. Performance Analysis and Sequencing are explored less frequently, while Feeding appears to be the least studied objective. It is important to note that the values shown in histograms can exceed the total number of articles analysed, since several studies face more than one objective simultaneously.

Shifting the focus to objective combinations analysed in relation to the Space characteristic, Fig. 11(b) highlights that the Design – Feeding combination is among the most frequently studied [26,27], along with Design – Balancing [22,23]. Regarding the Availability characteristic, shown in Fig. 11(c), a wide range of objective combinations is present. However, the most frequently analysed remain Design – Balancing [13, 22,23,39,42,43,46,49–51], as well as Sequencing – Performance Analysis [28,35], Design – Sequencing – Performance Analysis [29,34], and Design – Balancing – Sequencing [20,41]. For the Cost characteristic, illustrated in Fig. 11(d), the most common combination remains Design – Balancing [13,23,39,43,46,50,51,55,57,58,65], with Design – Balancing – Sequencing [20,67,68] also standing out among the other combinations. Examining the Performance characteristic, shown in Fig. 11(e), the

Design – Balancing combination again emerges as the most frequently analysed [12,22,43], followed by Design – Performance Analysis [53,59], Design – Balancing – Performance Analysis [74,75], and Design – Balancing – Sequencing [67,68]. Finally, for the People characteristic, illustrated in Fig. 11(f), the Design – Balancing combination continues to be the most studied [12,22,42,43,49,55], followed by Design – Feeding [26,27] and Design – Balancing – Sequencing [41,67].

From this analysis, it can be concluded that Balancing and Design are the most frequently considered objectives in the literature, particularly as the Design – Balancing combination. Sequencing and Performance Analysis are explored to a lesser extent but still hold significance, with Design – Balancing – Sequencing emerging as a classic problem in the literature, alongside the Design – Balancing – Performance Analysis combination.

Regarding variability, it is considered in about half the cases. As shown in Fig. 12, although line balancing is the most frequently discussed topic in the literature, the analysis reveals that its relative percentage within the studied context is the lowest. This suggests that, despite being a well-established and extensively researched area, its specific treatment in this context may be less in-depth compared to other aspects.

Moreover, when variability is analysed, studies tend to favour both components together. Otherwise, fewer articles implement operational time variability as a standalone factor, and even fewer consider market demand variability as the sole fluctuating element.

6.2. Exploring key methods

Moving on to the analysis of the most commonly adopted methodologies, these can be categorized into six main groups:

- **Integer Programming:** refers to a family of mathematical optimization models where decision variables are constrained to take on integer values. This family includes methods such as Integer Linear Programming (ILP), Mixed Integer Linear Programming (MILP), and Mixed-Integer Nonlinear Programming (MINLP). These techniques are especially well-suited for combinatorial problems that involve discrete choices and require precise, optimal solutions under a set of defined constraints.
- **Simulation:** virtual reproduction of the real system through computational models, allowing performance analysis and testing of different scenarios.

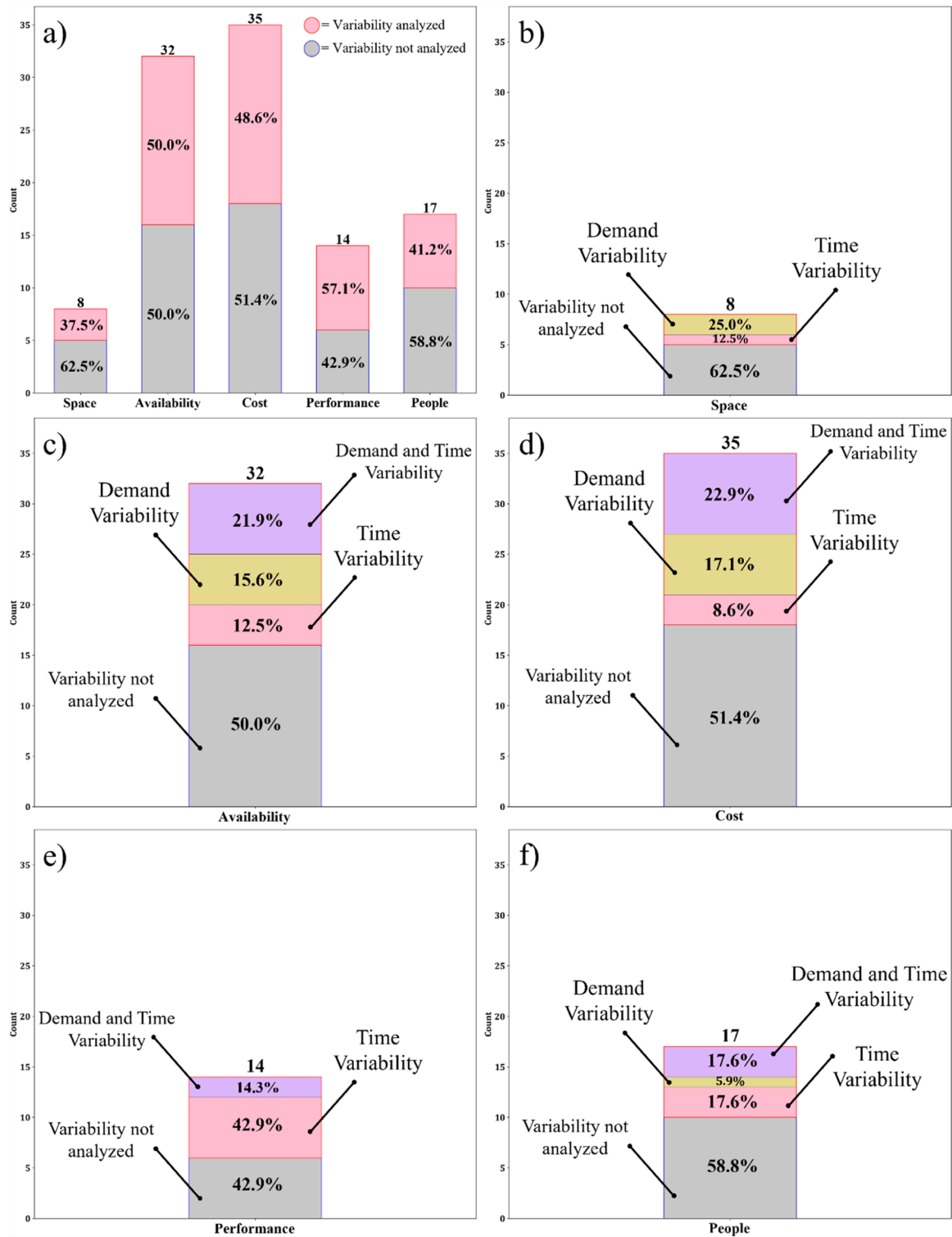


Fig. 10. (a) The histogram shows the percentage of articles that also integrate one or more variability components within the studied problem. (b) Breakdown of the Space group. (c) Breakdown of the Availability group. (d) Breakdown of the Cost group. (e) Breakdown of the Performance group. (f) Breakdown of the People group.

- *Meta-heuristics*: a set of optimization algorithms (e.g., Genetic Algorithm, Tabu Search) designed to find high-quality solutions within a reasonable time frame, without necessarily guaranteeing the absolute optimum.
- *Multi-Objective Function*: refer to methods developed to handle optimization problems with multiple, often conflicting, objectives. While multi-objective optimization can sometimes be solved using integer programming techniques when the decision variables are discrete, it

- is not confined to them. Thus, multi-objective function methods represent a broader category aimed at balancing trade-offs among different performance criteria, independent of the specific nature (integer or continuous) of the decision variables.
- *Machine Learning*: a data-driven approach that enables models to improve performance without explicitly predefined rules.
- *Approximate Analytical Models*: are a class of methods that use simplified mathematical representations to approximate the

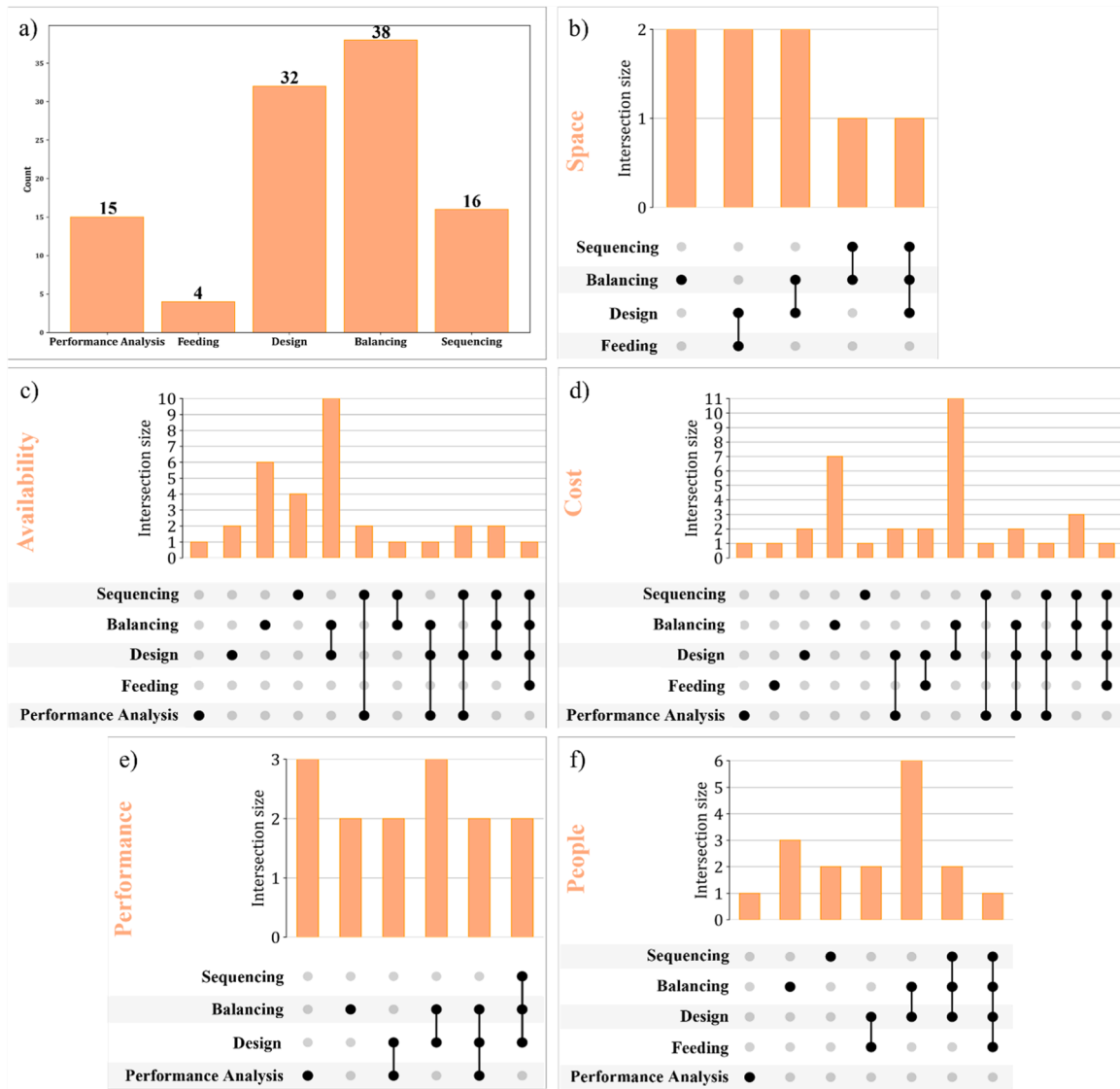


Fig. 11. (a) Histogram of the objectives addressed in the articles. (b) UpSet plot of the combinations of objectives in the Space group. (c) UpSet plot of the combinations of objectives in the Availability group. (d) UpSet plot of the combinations of objectives in the Cost group. (e) UpSet plot of the combinations of objectives in the Performance group. (f) UpSet plot of the combinations of objectives in the People group.

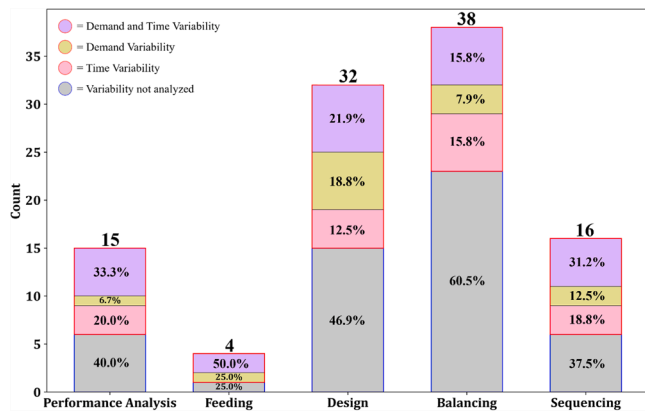


Fig. 12. Percentages of articles addressing variability grouped by objectives. Variability is broken down into variability that affects only operating times, only market demand, or variability that takes both components into account.

behaviour of complex systems, thereby reducing computational complexity while retaining key dynamics. These models often employ probabilistic frameworks or decompose the overall problem into more manageable sub-problems. Examples include methods such as Markov Decision Processes, Decomposition Approaches, and RFID-enabled Monitoring, among others.

In this case, as shown in Fig. 13(a), the most commonly used methods in Mixed Model and Multi Model problems related to resource management are Integer Programming and Meta-heuristics. This suggests that the highly combinatorial and constraint-driven nature of these problems favours robust and flexible optimization approaches. It is important to note that the values shown in histograms can exceed the total number of articles analysed, since several studies face more than one method simultaneously.

On one hand, Integer Programming provides exact (or near-exact) solutions but remains manageable only for relatively small problem instances. On the other hand, Meta-heuristics become advantageous as

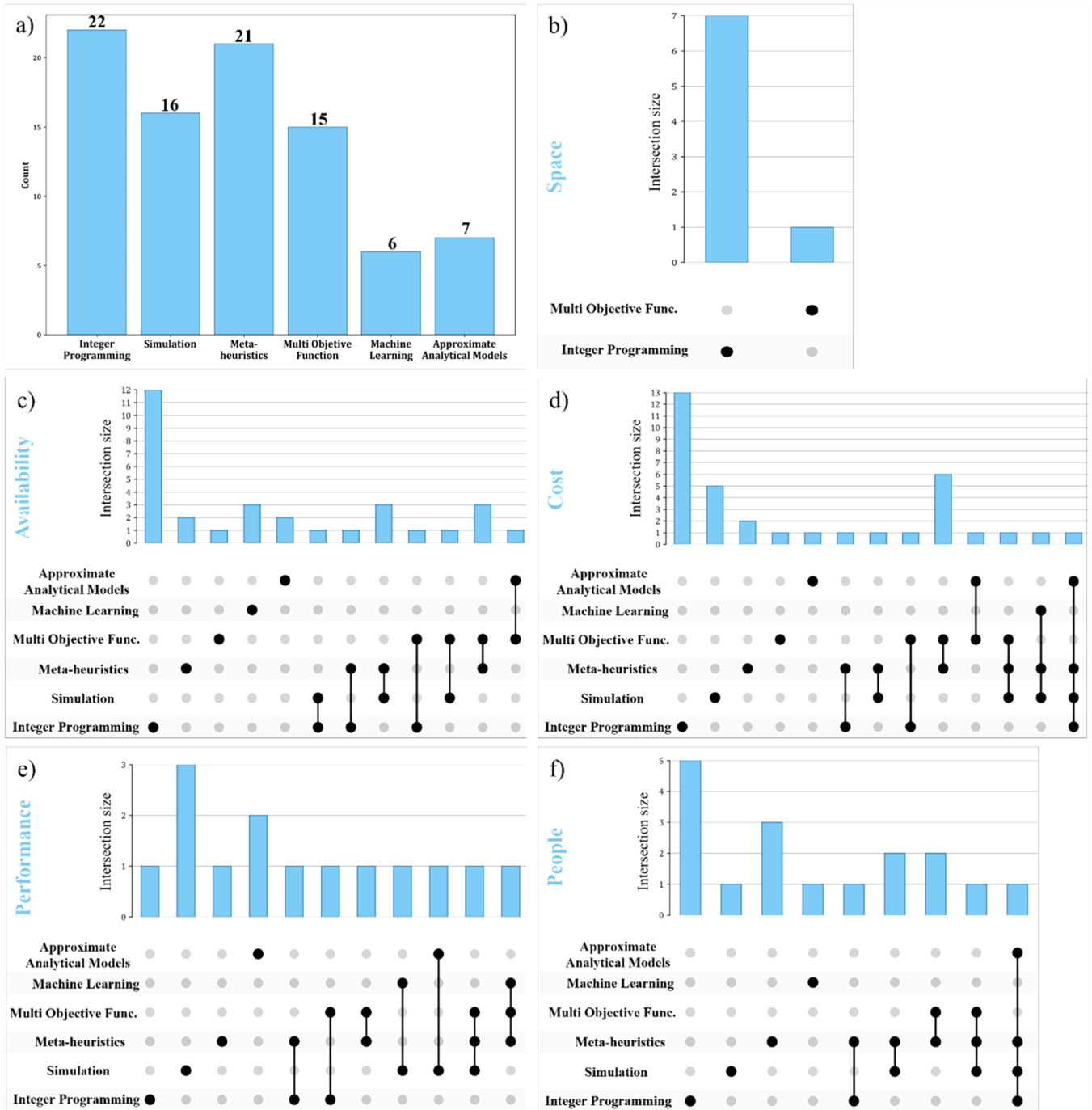


Fig. 13. (a) Histogram of the methods addressed in the articles. (b) UpSet plot of the combinations of methods in the Space group. (c) UpSet plot of the combinations of methods in the Availability group. (d) UpSet plot of the combinations of methods in the Cost group. (e) UpSet plot of the combinations of methods in the Performance group. (f) UpSet plot of the combinations of methods in the People group.

complexity increases, offering greater scalability at the cost of approximate solutions. Currently, one of the main limitations in this field is the relatively small size of problem instances addressed in the literature. However, new perspectives are emerging to extend these methodologies to larger-scale cases, better aligned with real industrial requirements. Simulation methods and multi-objective functions are explored less frequently in this context, while Machine Learning algorithms and approximate analytical models are currently the least adopted methods for resource management in Mixed Model and Multi Model environments. Shifting the focus to the most commonly used methods when considering the Space characteristic, Fig. 13(b) shows that Integer Programming is the most frequently adopted method [20–22,24–27],

followed by Multi-Objective Function [23]. In this case, no method combinations are observed. For the Availability characteristic, illustrated in Fig. 13(c), a variety of method combinations emerge, with the most frequently used being Meta-heuristic – Simulation [15,30,31,40] and Meta-heuristic – Multi-Objective Function [41,44,50]. Regarding the Cost characteristic, shown in Fig. 13(d), several method combinations are present, but Meta-heuristic – Multi-Objective Function stands out as the most frequently applied [44,55,62]. Examining the Performance characteristic, depicted in Fig. 13(e), the distribution appears rather uniform, with multiple distinct method combinations occurring only once each. Finally, for the People characteristic, shown in Fig. 13(f), the two most prominent method combinations remain

Meta-heuristic – Simulation [31,40] and Meta-heuristic – Multi-Objective Function [41,55].

Based on the review, Integer Programming (IP) and meta-heuristics are the most frequently applied techniques. Their prominence reveals a dual reality: research still gravitates toward small-scale, tightly controlled test beds, yet there is clear momentum toward methods that can cope with larger, more complex industrial contexts. Within hybrid studies, the pairing Meta-heuristic + Multi-Objective Function is most common, followed by Meta-heuristic + Simulation.

IP remains the gold standard while the decision space is compact: with only a few products and a short horizon, an IQP can reach optimal solutions in well under one second and enforce every precedence, layout, and capacity constraint, performance no heuristic can match [20]. Scalability, however, is its Achilles' heel: stretching the same model to ten periods drives runtime into the minutes and eventually makes larger instances infeasible, pushing the authors to suggest heuristic surrogates [20]. A similar wall is met in collaborative assembly-line balancing, where an MILP with just 29 tasks demands nearly two hours of computation and is explicitly tagged NP-hard, leaving bigger cases to future meta-heuristic work [42]. When the combinatorial space explodes, meta-heuristics step in. A particle-swarm hybrid can configure hundreds of modules, virtual units, and lines for a mass-personalisation plant in minutes, avoiding the intractability of a MILP [49]; likewise, a Genetic Algorithm with a “matrix” encoding balances mixed-model lines quickly enough to run in an SME-level spreadsheet [12]. These gains come at a cost: solution quality hinges on problem-specific parameter tuning and chromosome design, and optimality gaps remain unknown.

Finally, machine-learning techniques remain the least explored avenue within the PRISMA-filtered corpus, yet emerging studies already spotlight their potential and the hurdles that must be cleared. In particular, recent work shows that optimisation-ML hybrids encounter three intertwined challenges on the shop floor. Model complexity rises sharply when reinforcement-learning agents must coordinate many decision points: multi-agent RL for integrated line control demands careful credit assignment and hierarchical design to stay tractable [77], a difficulty also noted when neural networks are embedded in real-time AGV scheduling [78]. Explainability poses a second challenge: operators were reluctant to trust a deep-RL maintenance policy until its actions were clarified through post-hoc visual analytics [79], while physics-informed reward structures have been introduced to make policy logic more transparent [77]. Computational feasibility completes the triad; the inference budget needed for an online RL sequence planner to

adapt within cycle time has been quantified [80], and benchmark studies compare training times with heuristic baselines to verify shop-floor viability [79]. Taken together, these contributions confirm the promise of optimisation-ML hybrids yet underscore the practical barriers – complexity, opacity and runtime costs – that must be overcome before large-scale industrial adoption.

Shifting the analysis of variability to a methodological perspective, it is once again considered in most cases, as shown in Fig. 14. Similar to objectives analysis, studies on variability tend to favour both components together (“Both” category). When a single component is analysed, variable operational times are the most frequently studied aspect.

An interesting finding is that Machine Learning and approximate models are more commonly applied in problems characterized by high levels of uncertainty in demand and/or processing times. This is due to their flexibility and ability to adapt to dynamic scenarios. Specifically, Machine Learning leverages its capacity to learn patterns and relationships from data, allowing adaptation to evolving conditions [28,32,35,54,73,74]. In contrast, approximate analytical models simplify problem complexity while maintaining a sufficient degree of realism, making them more manageable for handling different sources of variability [15,34,36,37,53,71,75].

To conclude the analysis of objectives and methods, Fig. 15 synthesises their interplay for each resource-management dimension: Space, Availability, Cost, Performance and People. Objectives previously categorised in Chapter 6.1 (e.g., Design, Balancing, Sequencing) are shown as orange nodes, and methodological approaches introduced in Chapter 6.2 (e.g., Integer Programming, Simulation, Machine Learning) appear as blue nodes; in both cases the node diameter is proportional to the number of papers that address that category. An edge links an objective to a method whenever they co-occur in at least one study, and its thickness grows with the frequency of that pairing. Because a single article can pursue several objectives through multiple methods, the network is inevitably dense; to aid interpretation, only the most recurrent objective–method combinations within each resource group are colour-highlighted, whereas infrequent links remain in light grey. A legend beneath each sub-panel lists, in matching colours, the highlighted combinations, enabling the reader to trace any coloured edge back to the exact objective–method pair it represents.

This representation reveals the shift toward increasingly complex configurations, where multiple objectives and techniques interact to address intricate challenges. The dense network of connections highlights the progressive adoption of a more integrated and multidisciplinary approach.

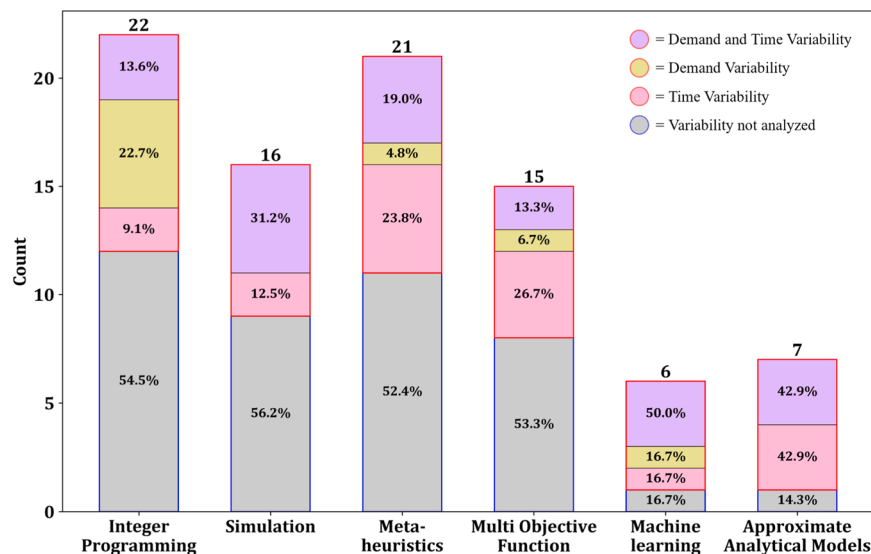


Fig. 14. Percentages of articles addressing variability grouped by methods. Variability is broken down into variability that affects only operating times, only market demand, or variability that takes both components into account.

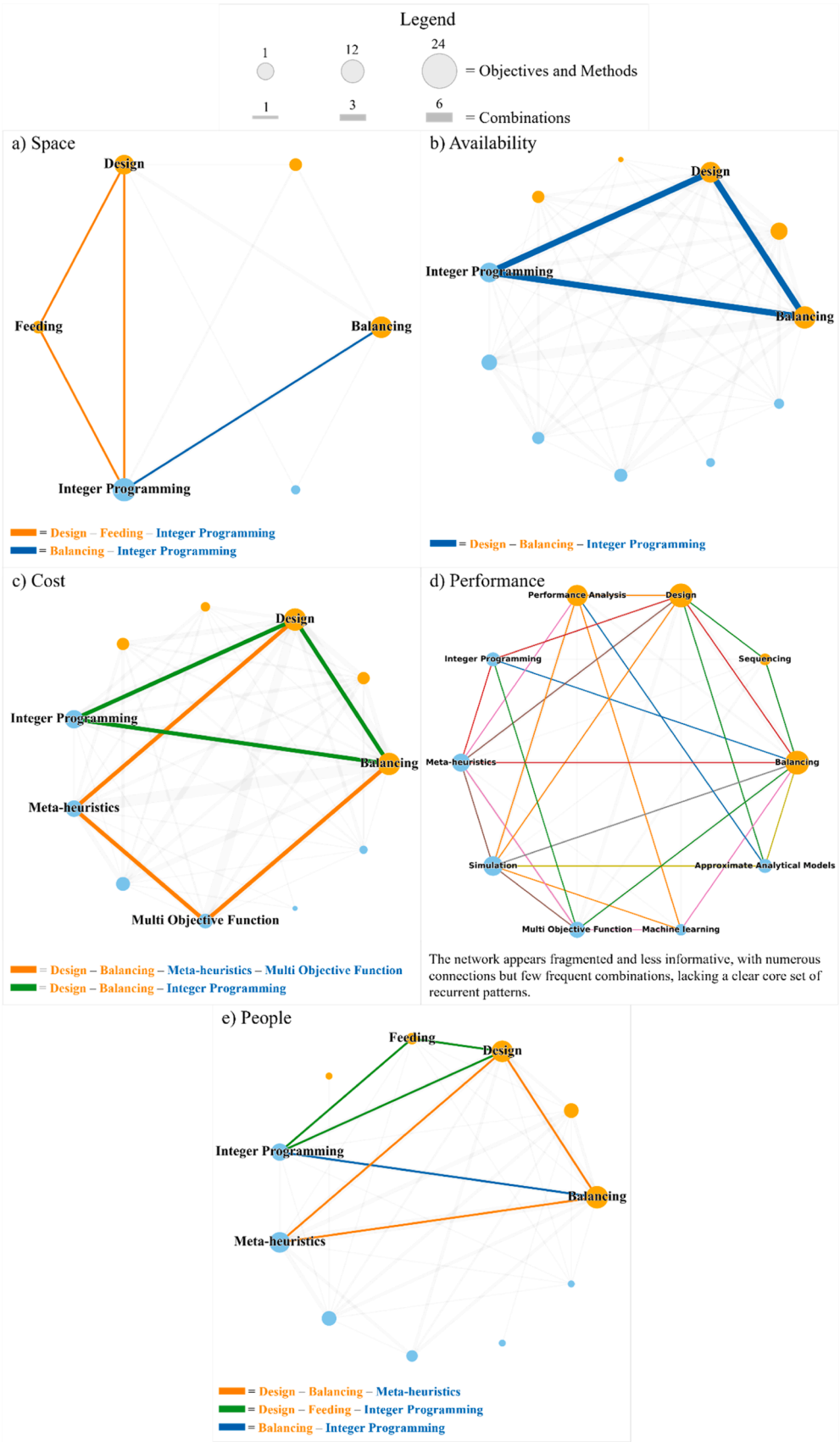


Fig. 15. Network Graph between objectives and methods. The background network (light grey) represents all the possible combinations that occur in the group. The coloured connections represent the most frequently used combinations in the group under examination: different colours refer to different combinations. (a) shows the most used combinations in the Space group. (b) shows the most used combinations in the Availability group. (c) shows the most used combinations in the Cost group. (d) shows the most used combinations in the Performance group. (e) shows the most used combinations in the People group.

In particular, the Space group, illustrated in Fig. 15(a), exhibits a limited number of combinations, with the most recurrent being Balancing – Integer Programming, as well as Design – Feeding – Integer Programming. Moving to the Availability group, shown in Fig. 15(b), a significantly larger number of combinations emerges, as evidenced by the dense network of connections. Here, Design – Balancing – Integer Programming appears as a frequently recurring combination. For the Cost group, depicted in Fig. 15(c), multiple objective-method interactions are also present. However, two dominant combinations stand out: the first is Design – Balancing – Integer Programming, while the second is Design – Balancing – Multi-Objective Function – Meta-heuristics. Regarding the Performance group, represented in Fig. 15(d), the network appears fragmented and less informative, with numerous connections but few frequent combinations, lacking a clear core set of recurrent patterns. This may be because the Performance category encompasses a wide range of potential scenarios and methodological approaches, making it inherently more generic. Finally, as shown in Fig. 15(e) for the People group, three primary frequent combinations emerge: Design – Feeding – Integer Programming, Balancing – Integer Programming, and Design – Balancing – Meta-heuristics.

For full reference, the complete tables of all examined articles and their categorizations are provided in Appendix A, which presents the classification of the analysed papers based on the resource characteristics examined, and in Appendix B, which includes the classification based on the addressed variability, analysed objectives, and applied methodologies.

6.3. Interactive mechanisms: Matching resource heterogeneity to algorithm families

To clarify the resource taxonomy underpinning our analysis, we first distinguish three macro-types commonly found on the shop floor:

- Humans: skilled operators who perform, supervise, and adapt tasks in real-time.
- Machinery: the primary process machines or workstations that execute the core transformational steps.
- Auxiliary Equipment: tooling, fixtures, material-handling devices, inspection instruments and other support assets that enable or enhance production but do not themselves carry out the main process.

Building on this taxonomy, the review moves beyond a simple catalogue of resources and optimisation techniques by examining how resource heterogeneity interacts with algorithm choice. We therefore group the studies into three incremental heterogeneity levels. Level 1 models only one resource category: humans, machinery or auxiliary equipment, so no cross-class interaction arises. Level 2 combines two categories (for example, operators plus machines), introducing limited coordination across classes. Level 3 embraces fully multi-resource settings that consider humans, machinery and auxiliary equipment simultaneously, generating the greatest combinatorial complexity. Each paper is then matched to its predominant method family (MILP/IP, meta-heuristic, simulation, machine learning, etc.), allowing us to reveal systematic links between the richness of the resource model and the optimisation approach selected.

Fig. 16 summarises these shifts. Level 1 studies show a fairly even spread: integer-programming models and discrete-event simulation account for the largest shares, while meta-heuristics, multi-objective formulations and machine-learning approaches follow at similar but lower levels; only approximate analytical models appear seldom, confirming that purely closed-form approximations are now rare once even a single resource class is modelled in detail. In Level 2, where a second resource class must be co-ordinated, integer programming regains a clear lead. Most authors extend mono-resource MILP formulations by adding binary assignment variables or disjunctive capacity constraints, an approach that keeps the model structure compact while capturing the extra interaction. Simulation still feature, but mainly as benchmark or hybrid accelerator rather than the primary solver. The landscape changes decisively in Level 3. When humans, machines and equipment interact simultaneously, meta-heuristics become the default option; their share more than doubles because they can navigate the combinatorial explosion generated by multi-resource precedence, ergonomic and availability constraints. Multi-objective formulations often accompany these searches, allowing authors to reconcile competing criteria (throughput, ergonomic risk, change-over effort) in a single run. Integer programming falls back to a supporting role – used mainly in decomposition or as a local improvement stage – while simulation supplies scenario validation and machine-learning begins to appear in adaptive, data-rich settings.

These observations suggest that algorithm choice may correlate with the degree of resource heterogeneity: exact solvers tend to suffice in narrowly scoped problems, whereas flexible search and learning techniques become increasingly common as the number of interacting resource

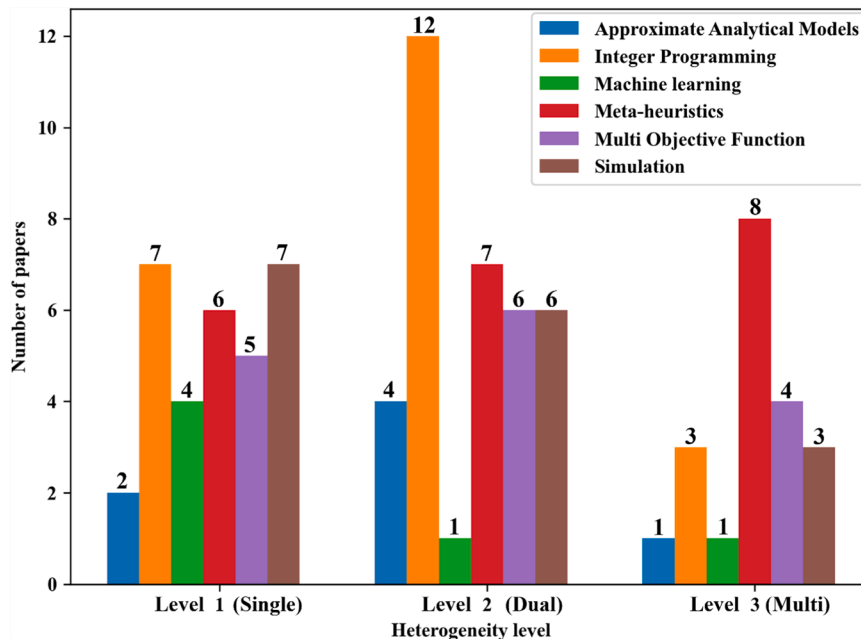


Fig. 16. Bar chart showing, for each resource-heterogeneity level (single, dual and multi), the number of papers that adopt a given family of optimisation techniques.

classes and, with it, the operational richness of the assembly line grows.

At Level 1 (single-resource problems) the preferred tools are still integer-programming models – mostly ILP formulations solved by branch-and-bound – and discrete-event simulation, typically implemented in commercial DES packages. At Level 2 (two resource classes) the field converges even more strongly on MILP formulations; many authors embed Benders decomposition or couple MILP blocks with constraint-programming phases (IP + CP) to keep model size manageable while capturing the new cross-resource links [81]. At Level 3 (three interacting resource classes) the spotlight shifts to meta-heuristics. Genetic-algorithm variants such as SPEA-II or Adaptive GA are the workhorses, with Particle Swarm Optimisation and Ant Colony Optimisation used as complementary search engines when problem size or rugged objective landscapes defeat exact solvers [82]. Table 2 summarizes some examples of the most used algorithms in relation to the levels of resource heterogeneity.

6.4. An industry 5.0 perspective

To round off the discussion, we offer a concise reflection through an Industry 5.0 lens. Industry 5.0 reframes smart manufacturing around three complementary pillars – human-centricity, resilience and sustainability – whose aim is to transform flexible, data-driven lines into socially and environmentally responsible systems [2]. Accordingly, each paper in our PRISMA corpus was coded for the presence of (i) operator-centred features, (ii) explicit robustness or disruption modelling and (iii) quantified environmental impacts. Thirty-five of the 59 studies map to at least one pillar: 52 % target resilience, 31 % human-centricity and only 17 % environmental sustainability, confirming a strong bias toward volatility-mitigation and a clear gap on environmental metrics. Note that papers may address multiple pillars simultaneously, explaining why individual counts exceed the total corpus when summed.

Fig. 17 refines this perspective by linking the five resource characteristics to the same pillars. People-oriented work is, unsurprisingly, almost entirely human-centric. Cost and Performance studies lean heavily toward resilience, using these metrics to harden lines against demand swings and failures. Space and Availability split their emphasis: roughly equal shares treat them as ergonomic (layout safety, operator reach) or resilient (buffer sizing, uptime strategy), while only a small fraction ties floor area or capacity decisions to explicit sustainability goals.

Overall, current resource-management research aligns well with the human-centric and resilience ambitions of Industry 5.0 but addresses sustainability only marginally. Bridging this gap – by embedding energy, circular-economy or life-cycle-costing indicators into the same optimisation models – remains an open avenue for future work. At the same time, the field must continue deepening its attention to the human dimension: leveraging human capital is central to the Industry 5.0 transition, recasting workers as active enablers of innovation rather than passive recipients of technological change [11]. Fostering both sustainability and human-centricity alongside resilience will ensure that all three pillars advance in concert.

7. Identified limitations and proposal of a research agenda

Finally, this chapter addresses the limitations and potential developments of Resource Management in MMAL and MuMAL contexts. Many studies oversimplify models, neglecting the inherent variability of production systems, and rely on limited real-world scenarios for validation, which casts doubt on their practical applicability. Additionally,

research often focuses on isolated problems and a narrow set of characteristics (e.g., only spatial requirements or resource costs) rather than adopting an integrated view of resource management challenges.

A further gap is the limited focus on uncertainty arising from demand fluctuations, machine failures, and unforeseen changes in production lines, which reduces the robustness of the proposed models. Many studies employ simplified assumptions – deterministic production cycles, uniformly equipped resources, or negligible setup times – that do not capture the intricacies of real-world systems [43,56]. Moreover, numerous line-balancing studies assume a single worker per workstation, restricting the ability to manage multi-model settings and dynamic task assignments [15].

In addition, vital aspects such as cognitive stress, ergonomics, and worker adaptability in human-robot collaborative lines are still insufficiently examined, despite their importance in many manufacturing environments [55].

Validation is often confined to narrow datasets or simulation settings, with minimal real-world or large-scale testing [22,27,59]. Many studies restrict validation to small-scale cases, casting doubt on the scalability of the proposed solutions [20,35,68]. This undermines confidence in the robustness of these approaches, an issue further intensified by the absence of extensive industrial trials [25,34,61].

Research on Mixed Model and Multi Model assembly lines frequently highlights the difficulty of merging configuration and scheduling within a single decision-making framework. Studies often neglect scheduling or assume constant conditions, such as unvarying setup times, fixed operation sequences, or homogeneous equipment and skills [24,42,68]. Although some innovative approaches have been introduced, they typically focus on specific aspects of assembly line management. For example, certain models prioritize the physical arrangement of resources while overlooking the integration of digital elements – such as cloud solutions – that could enhance flexibility and responsiveness [49]. Similarly, novel tools like Manufacturing Maps show considerable potential for real-time monitoring and management of resources, but require further research to effectively identify bottlenecks and dynamically adjust robot speed, thereby optimizing energy consumption [56].

To overcome these limitations, future research directions should aim to address the following themes.

In terms of addressing variability, research indicates that multi-product strategy management and multi-objective approaches, combined with stochastic elements and safety stock policies, can enhance resilience [51]. Extending models to additional lines, products, and demand fluctuations is also proposed to capture a broader range of operational scenarios [27]. Meanwhile, hybrid methods that couple mathematical optimization, agent-based simulation, and machine learning can more effectively handle stochastic phenomena and multiple variables, including new products, evolving demand, and variable setup times [62]. Investigating stochastic uptime, machine failures, and repair patterns [13], as well as integrating simulation and machine learning to manage variability, setup time variations, and resource allocation [32, 70,73], further broadens the scope of future research.

Moving on to flexibility and reconfigurability, the development of reactive strategies is essential to quickly adapt to demand changes and unforeseen events, a point confirmed by a twin-driven rolling rescheduler that cut makespan 12 % during rush-order shocks in an ETO line [37,83]. The creation of IT systems for algorithmic models, alongside digital resources and cloud-based solutions, can facilitate real-time data processing and improve system adaptability across various industrial settings, as recent digital-twin pilots showed, trimming data-collection latency yet

Table 2
Most common optimisation families by heterogeneity level.

Type of Heterogeneity	Number of papers	Most used family solutions	Example of most used solutions
Level 1	21	Integer Programming, Simulation	ILP, BB, BB&R, DES
Level 2	27	Integer Programming	MILP, Bender's Decomposition + MILP, IP + CP
Level 3	11	Meta-heuristics	GA, NSGA, SPEA- II, AGA, PSO, ACO, TS, COMSOAL

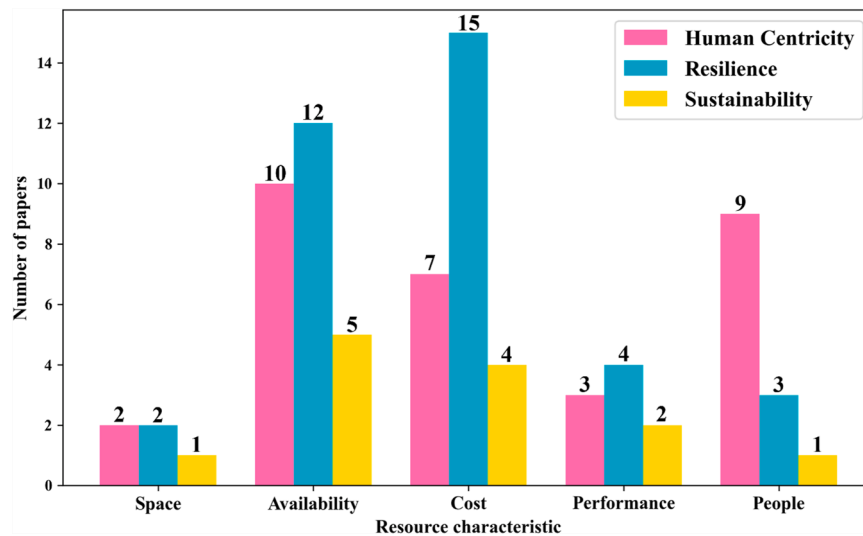


Fig. 17. For each characteristic (Space, Availability, Cost, Performance, People) the bars show the number of reviewed papers that address it from a human-centric, resilience or sustainability perspective.

exposing cloud bottlenecks in real aerospace assembly [49,84,85]. Exploring decentralized kitting options, combined with reconfigurability and production control, offers additional avenues for dynamic decision-making [26]. Meanwhile, building flexible and resilient assembly systems allows rapid responses to production variations and operational disruptions [56], and adopting a flexible sequence of operations [20] or metaheuristic and machine learning approaches [20,24,42] further enhances the ability to handle large-scale, diverse environments.

Turning to human factors, there is a need for more comprehensive assessments of ergonomic parameters, including posture-related risks and cognitive stress caused by specific tasks [1,45,55]. At the same time, workforce reconfiguration strategies that leverage flexible personnel and technologies, such as teleoperation and augmented reality, can bolster operational adaptability [15]. For instance, one study applied wearable-derived proficiency matrices to reassign tasks in real time and achieved an 8 % throughput increase on a home-appliance line [86].

Focusing on resources, instrumentation, and machinery, researchers propose accounting for non-uniformly equipped production lines, acknowledging that real-world settings often feature diverse equipment [42,68]. Developing optimization models for high-risk resources [35], reducing equipment costs, and implementing resource-sharing strategies [36], as well as incorporating additional constraints such as ergonomics, energy consumption, and sustainability, are all vital steps toward more realistic and comprehensive approach to variable and complex production environments [23,31,73].

In conclusion, regarding applications in real-world settings, employing these models in actual industrial environments with a larger number of tasks and robust generalization capabilities remains a key objective [20,42]. Efforts to design methods that address large-scale instances [45,47,55] are particularly important for bridging the gap between theoretical frameworks and practical demands.

We have grouped the principal future developments into macro thematic areas, as illustrated in Table 3. Each area underscores key open questions and possible trajectories for advancing both theory and practice. While these themes address diverse aspects of modern assembly lines systems, they are interlinked and can be “assembled” into a coherent research challenge that mirrors real industrial complexity. The Table 3 below offers a succinct overview of these future pathways. It is intended as a reference for researchers and practitioners alike, providing a research agenda of potential directions. The ultimate goal is to merge insights from multiple streams to tackle genuinely complex, multifaceted assembly lines problems.

For instance, “Developing optimization models for high-risk

resources” can be combined with “Investigation of the potential of operational reconfiguration” and “Studying non-uniformly equipped production lines”, a particularly pressing concern for industries seeking to optimize capital investments for better use of their assets.

Layout-aware optimisation – through reconfigurable workstations or smart rebalancing in fixed lines – adds another lever for resilience, lowering space and flow costs while preserving throughput during demand swings [87,88]. Integrating these dimensions aligns with current theoretical advances in optimisation and simulation and, at the same time, reflects the practical priorities of industry stakeholders. IIoT-enabled sensing and connectivity are already moving such concepts onto the shop floor: high-frequency data streams feeding digital twins compress decision latency and cut downtime on pilot lines, while wearable-derived proficiency metrics have boosted productivity in high-mix assembly contexts [84–86]. Embedding both layout-aware optimisation and real-time analytics within holistic resource-management frameworks is therefore essential for truly self-adapting MMAL and MuMAL systems. Edge-cloud latency, data governance and cyber-security, however, remain open challenges that call for sustained academic–industrial collaboration and large-scale validation, ensuring these solutions are not only theoretically sound but also scalable and feasible in real production environments.

8. Conclusion

The systematic review of the literature offers significant insights into the management of critical resources and variability in MMALs and MuMALs, their integration within objectives and methods, and the limitations and future directions identified by the research community.

In response to RQ1, the literature review indicates that Resource Management in MMALPs and MuMALPs production contexts can be organized into five main categories: Space, Availability, Cost, Performance, and People. Among these, the most prominently discussed are resource costs and resource availability, particularly in terms of ensuring timely resource usage. In contrast, Space remains the least explored category at present. Within each category, Space is typically treated as a constraint in problem formulations. Availability is primarily examined in the context of scheduling, where resources are allocated dynamically, and their availability evolves over time. The Cost category mostly addresses partial cost analyses, focusing on specific cost components (e.g., labour or equipment) rather than a comprehensive cost structure. In the Performance group, the emphasis is generally on production-oriented and economic measures, with only a few studies proposing KPIs to assess ergonomic considerations. Finally, in the

Table 3
Main limitations in resource-centric MMALs and MuMALs studies and corresponding avenues for future research.

Limits	Future Researches
Oversimplify models Assuming simplifying assumptions to reduce mathematical complexity due resource requirements. In particular, all lines have the same number of stations, is not possible to walk between stations, all cobots have the same function, all lines are equipped in the same way with homogeneous equipment [42,43,48].	- Adopting a flexible sequence of operations [20]. - Studying non-uniformly equipped production lines, acknowledging that real-world settings often feature diverse equipment [42,68]. - Developing optimization models for high-risk resources [35]. - Extend model to account for the workload of various resources and other factors, in order to represent more complex cellular manufacturing systems [31]. - Integrate layout-aware optimisation that jointly determines task assignment, part-feeding policy and floor-space sizing, showing that co-optimising these decisions can lower total cost and improve space utilisation [87].
Neglecting variability Activity completion times for all products are deterministic and known in advance [6, 42,70].	- Study hybrid methods that combine mathematical optimization, agent-based simulation, and machine learning to handle stochastic phenomena [32,62,70]. - Explore cost implications of adapting to uncertain demand and variable line availability scenarios [23]. - Extend models to incorporate sudden demand spikes driven by specific events [23]. - Investigation of the potential of operational reconfiguration, that can be considered by the developed approach through the notion of adjustment times between tasks and resources [68,88]. - Explore IIoT-enabled digital-twin platforms that support rolling rescheduling and rapid response to breakdowns, rush orders and product-mix changes [83,84].
Limited real world scenarios - Restrict validation to small-scale cases [31,35,68]. - Absence of extensive industrial trials [25,49,61].	- Study metaheuristic and machine learning approaches further enhances the ability to handle large-scale, diverse environments [20,24,42]. - Employing these models in actual industrial environments with a larger number of tasks and robust generalization capabilities remains a key objective [20,42].
Few human factors examined Cognitive stress, ergonomics, and worker adaptability in human-robot collaborative lines are still insufficiently examined [55].	- Include posture-related risks and cognitive stress caused by specific tasks [1,45,55]. - Analyze reconfiguration strategies that leverage flexible personnel and technologies, such as teleoperation and augmented reality, can bolster operational adaptability [15]. - Incorporate wearable-sensor data to build dynamic proficiency models that guide real-time worker–task assignment and ergonomically informed decision-making [86].

People group, research is largely centred on operator skills and efficiency. When multiple characteristics are studied simultaneously, there is a tendency to prioritize aspects related to both cost and availability. Less prevalent but still noteworthy are studies that consider human factors in conjunction with availability.

Regarding **RQ2**, the literature review indicates that variability in MMALPs and MuMALPs can be categorized into two main types: variations in operational times, referred to as *internal variability*, and fluctuations in market demand, referred to as *external variability* – which are the most commonly investigated. Roughly half of the contributions in each category address at least one of these aspects, either focusing exclusively on time variability or examining both time- and demand-related variability together. Fewer studies concentrate solely on demand variability. The least explored aspects in variable environments appear to be resource space and human factors.

Finally, in response to **RQ3**, the literature shows that in MMALPs and MuMALPs where resources play a central role, the most commonly addressed goals are line design and line balancing, while feeding policies receive comparatively less attention. Regarding the methods, integer programming and metaheuristics are the most frequently used approaches. Currently, machine learning remains the least explored technique. Concerning the combinations of objectives and methods, when space characteristics are examined, two main topics emerge as the most extensively covered: (i) line balancing addressed using integer programming techniques, and (ii) line design aimed at determining the best feeding strategies, also solved through integer programming. Similarly, studies focusing on resource availability tend to address the problem through a combination of objectives: line design and line balancing, typically solved using integer programming techniques. Moving to the cost-related characteristics of resources, two main objective–method combinations are most frequently studied: (i) as before, the line design and balancing problem, typically solved using integer programming, is one of the most commonly analysed; (ii) the same combination of

objectives – design and balancing – is also addressed using multi-objective functions with metaheuristic approaches. Concerning performance-related aspects, the most common combinations of objectives and methods are not clearly identifiable, as there are many. However, the most frequently studied objectives include line balancing problems and the overall evaluation of line performance. The most commonly used methods are simulations and approximate analytical models. To conclude, studies focusing on human factors tend to explore the combination of line design and balancing, using either integer programming or, alternatively, metaheuristic approaches. Additionally, line design aimed at determining the best feeding strategies – typically solved using integer programming – is also addressed in this context.

From the standpoint of both goals and methods, roughly half of the contributions address elements of variability, typically involving fluctuations in both operational times and market demand. Concerning the space group, design and feeding objectives often employ integer programming. Alternatively, line-balancing problems in this group are also tackled via integer programming. Resource availability studies emphasize integer programming methods for design and balancing; a comparable approach applies to cost-focused research, which relies heavily on integer programming for design and balancing while also incorporating metaheuristics with multi-objective techniques. In the performance group, the primary concern is performance analysis, as anticipated, primarily through simulation or approximate analytical models. Finally, studies addressing human factors generally concentrate on design and line-balancing using metaheuristics, although integer programming is also deployed, especially for design, feeding, and exclusive balancing problems.

8.1. Theoretical contributions and practical implications

The present study makes a theoretical contribution by offering a new, resource-centric and variability-focused perspective on MMALs and MuMALs. Specifically:

- *Unified Resource – Variability Framework*: we establish a conceptual framework that systematically organizes resources into five categories (space, availability, cost, performance, and people factors) and incorporates both internal (e.g., processing times) and external (market demand) variability. By doing so, we address a notable gap in the literature, which often examines these dimensions in isolation, and highlight how their interplay shapes the design and operation of MMALs and MuMALs.
- *Consolidation of Objectives and Methods*: We systematically map how key objectives are approached through various methodological families. This mapping is further differentiated by the type of resource characteristic under study and by the presence or absence of variability. As a result, we reveal which objective – method combinations dominate in current research to address different resource features and levels of uncertainty, highlighting where established approaches prevail, and where emerging techniques remain underexplored.
- *Identification of Underexplored Areas*: we highlight underexamined areas and show why these are crucial for next-generation assembly lines. By positioning these gaps within our integrated framework, we provide a clear agenda for researchers seeking to develop more robust, scalable, and human-focused solutions, thus strengthening the link between theoretical models and industrial needs.

From a practical perspective, the insights from this review suggest tangible guidelines for manufacturing practitioners (e.g., operations managers, process engineers, etc.) seeking to enhance efficiency in dynamic assembly contexts:

- *Integrated Resource and Variability Management*: early-stage planning should anticipate both internal and external fluctuations to prevent downstream inefficiencies. For instance, modular workstations, cross-trained operators, and real-time monitoring can mitigate the risks posed by uncertain demand or processing times.
- *Holistic Consideration of Resource Characteristics*: managers should avoid siloed approaches by jointly accounting for multiple resource dimensions when configuring assembly lines. Such multifaceted planning supports more balanced and adaptable systems, ensuring that trade-offs in one resource area (e.g., cost) do not undermine another (e.g., workforce well-being).

8.2. Limitations and future developments of literature review

These conclusions are fully consistent with the key challenges raised in the introduction, where we underscored the increasingly customized and flexible nature of modern production systems. As businesses gradually move toward Industry 5.0, embedding advanced digital technologies and resource-focused models becomes indispensable for enhancing responsiveness and competitiveness. In sum, a well-structured, resource-centric, and variability-aware approach emerges as essential for transforming mixed or multi-model assembly lines into resilient systems aligned with the core principles of flexibility and reconfigurability. Beyond these structural considerations, whereas LCA indicators address environmental impacts across the product's life, production-line sustainability must also account for the production system's life-cycle costs and emissions, including construction, reconfiguration and decommissioning phases.

Despite providing an integrated view of resource management and variability in MMALs and MuMALs, this study has several limitations:

- *Stochastic Modelling Approaches*: the review does not explore how stochastic behaviours are introduced into MMALPs and MuMALPs, nor does it categorize the specific methods (e.g., probability distributions, Monte Carlo techniques, etc.) employed to represent randomness in factors such as processing times or demand patterns.

- *Distinction Between MMALs and MuMALs*: the analysis does not investigate whether there are meaningful differences in objectives, methods, or resource characteristics across the two main classes of assembly lines. It remains unclear if one type systematically prioritizes certain resource aspects or employs different sets of solution techniques.
- *Layout Configurations*: the study does not delve into layout variations (e.g., parallel lines, single straight lines, U-shaped lines, etc.), even though these configurations could yield substantial differences in how resources are managed and how variability is accommodated.

Building on these limitations, future research might address the following avenues:

- *Deeper Examination of Stochastic Modelling*: future research might systematically investigate how variability is generated and represented in MMALPs and MuMALPs. Rather than focusing on how to manage or mitigate uncertainty, the emphasis would be on understanding which probability distributions (e.g., normal, exponential, beta, etc.) or random generation frameworks are most commonly used, and why.
- *Clear Differentiation Between MMALs and MuMALs*: future reviews and empirical analyses might categorize studies according to whether they address MMALs and MuMALs, using tailored classification criteria that uncover distinctive challenges and solution strategies unique to each category.
- *Categorization by Layout Types*: lastly, further research could systematically filter the literature based on the line configurations (e.g., parallel vs. sequential lines, U-shaped layouts). Differentiating by layout could illuminate unique managerial considerations or technical constraints and offer more refined guidelines for line design under varying production requirements.

CRedit authorship contribution statement

Mario Tucci: Writing – review & editing, Visualization, Validation, Supervision. **Italo Cesidio Fantozzi**: Writing – review & editing, Visualization, Validation, Supervision. **Filippo De Carlo**: Writing – review & editing, Visualization, Validation, Supervision. **Mattia Gianassi**: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Leonardo Leoni**: Writing – review & editing, Visualization, Validation, Supervision, Methodology, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT by OpenAI in order to revise writing errors, suggest synonyms, and assist with translations into English. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Declaration of Competing Interest

The authors certify that there are no financial or personal conflicts of interest that could have influenced the content or conclusions of this manuscript.

Appendix A. - Classification of the analysed papers based on the resource characteristics examined

Authors	Year	Space	As a cost	As a constraint	Availability	Dynamic variable	Static variable	Design factor	Cost	Generic Analysis	Partial Analysis	Multi-Component Analysis	Performance	Production-oriented	Human-oriented	Complexity & Monitoring	Human	Efficiency	Well-Being	Discussed not in - depth
Oesterle J.; Amodeo L.	2016				X			X	X			X								
Stauder M.; Kuhl N.	2022				X	X														
Yang C.; Gao J.; Li J.	2014								X		X									
Stecke K.E.; Mokhtarzadeh M.	2022	X		X	X		X						X		X		X		X	
Güngör M.; Akç S.	2014								X	X										
Chen B.; Wang L.; Yu S.; Wan J.; Xia X.	2024												X			X				
Busagi M.; Ransikarbun K.; Oh Y.G.; Kim N.	2017								X	X			X			X				
Zhou B.; Zha W.; Ye L.; He Z.	2022								X	X										
Wang K.-J.; Eunike A.; Kurniawan I.; Ardi R.; Chiu J.-M.	2023				X	X														
Liu Q.; Song J.; Lv J.; Tang O.; Zhang Z.	2022												X	X						
Anel J.I.; Català P.; Serra M.; Domenech B.	2022												X	X			X			X
Mura M.D.; Dini G.	2023								X	X							X		X	
Morariu C.; Morariu O.; Borangiu T.	2014								X			X								
Tiacci L.; Mimmi M.	2018								X			X	X		X		X		X	
Jiang Y.; Wang D.; Xia W.; Li W.	2022				X	X			X	X										
Nishi T.; Kurakado H.; Liu Z.	2024				X	X											X	X		
Guo Y.; Zhang W.; Qin Q.; Chen K.; Wei Y.	2023												X			X				
Hashemi-Petroodi S.E.; Thevenin S.; Kovalev S.; Dolgui A.	2020				X			X	X		X									
Fisel J.; Lanza G.	2016				X			X	X			X								
Alghazi A.; Kurz M.E.	2018	X		X	X		X										X		X	
Wang L.; Liu H.; Xia M.; Wang Y.; Li M.	2024				X	X											X			X
Oesterle J.; Bauernhansl T.; Amodeo L.	2016								X			X								
Lopes T.C.; Brauner N.; Magalhães L.	2022	X	X						X		X									
Hashemi-Petroodi S.E.; Thevenin S.; Dolgui A.	2022				X			X	X			X								
Mazghani Y.; Hashemi-Petroodi S.E.; Thevenin S.; Dolgui A.	2024				X			X	X			X								
Razali M.M.; Ab Rashid M.F.F.; Make M.R.A.	2016				X		X													
Basin N.P.; Achkar V.G.; Méndez C.A.; García-Del-Valle A.	2017				X	X														
Hashemi-Petroodi S.E.; Thevenin S.; Dolgui A.	2024				X			X	X		X						X	X		
Hashemi-Petroodi S.E.; Thevenin S.; Kovalev S.; Dolgui A.	2022				X		X		X		X									
Ali I.; Ghanem N.; Fars M.N.	2020								X		X									
Gultekin H.; Tula A.; Selim Aktürk M.	2016				X	X			X		X									
Wu Y.; Zhao X.; Xu Y.; Chen Y.	2020								X		X									
Llopis J.; Lacasa A.; García E.; Montès N.; Hilario L.; Viscaino J.; Vilar C.; Vilar J.; Sánchez L.; Latorre J.C.	2022								X	X										
Zhang X.; Ming X.; Bao Y.	2022				X			X									X			X
Papakostas N.; Pintzas G.; Giannoulis C.; Nikolakis N.; Chrysosouris G.	2014								X	X										
Yang Z.; Xu W.; Wang P.-K.; Wang X.	2015				X	X			X		X									
Coelho F.; Macedo R.; Relvas S.; Barbosa-Póvoa A.	2022												X	X						
Oesterle J.; Amodeo L.	2014				X			X	X		X									

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Sadeghi P.; Rebelo R.D.; Soeiro Ferreira J.	2017			X	X					X	X
Sadeghi P.; Rebelo R.D.; Ferreira J.S.	2018			X	X					X	X
Alhamaidi E.; Askin R.G.	2024	X	X	X	X	X	X				
Qin Y.	2023					X	X				
Caputo A.C.; Pelagagge P.M.; Salini P.	2015	X	X			X	X			X	X
Low E.K.W.; Yung W.K.C.	2017							X	X		
Chen J.C.; Chen Y.-Y.; Chen T.-L.; Kuo Y.-H.	2019			X	X					X	X
Wang L.; Liu H.; Xia M.; Wang Y.; Li M.	2023			X	X						
Rane A.B.; Sunnapwar V.K.; Chari N.R.; Sharma M.R.; Jorapur V.S.	2017					X	X	X	X	X	X
Colledani M.; Ratti A.; Senanayake C.	2015			X	X						
Zhao C.; Li J.	2014							X	X		
Mukalay T.A.	2020					X	X	X	X		
Huang J.; Chang Q.; Arinez J.	2020					X	X				
Caputo A.C.; Pelagagge P.M.; Salini P.	2015	X	X			X	X			X	X
Yelles-Chaouche A.R.; Gurevsky E.; Brahimi N.; Dolgui A.	2024			X	X	X	X				
Koskinen J.; Raduly-Baka C.; Johnsson M.; Nevalainen O.S.	2020	X	X	X	X						
Uzunosmanoglu M.; Rao B.; Limère V.; De Cock A.; Singh Y.; Lopez A.J.; Gautama S.; Cottyn J.	2021	X	X	X	X	X	X				
Keshvarparast A.; Katiraei N.; Pirayesh A.; Battola O.; Berti N.	2023			X	X					X	X
Stief P.; Burgat G.; Pour-Massahian-Tafti M.; Dantan J.-Y.; Siadat A.	2023					X	X	X	X		
Pereira J.	2018			X	X	X	X	X	X	X	X
Manzini M.; Demeulemeester E.; Urgo M.	2022			X	X						

Appendix B. - Classification of the analysed papers based on the addressed variability, analysed objectives, and applied methodologies

Authors	Year	Variability	Time Variability	Demand Variability	Both	Performance Analysis	Feeding	Design	Balancing	Sequencing	Integer Programming	Simulation	Meta- heuristics	Multi Objective Function	Machine learning	Approximate Analytical Models
Oesterle J.; Amodeo L.	2016	X	X						X				X	X		
Stauder M.; Kühl N.	2022	X		X		X				X						X
Yang C.; Gao J.; Li J.	2014								X		X					
Stecke K.E.; Mokhtarzadeh M.	2022							X	X		X					
Güngör M.; Alaş S.	2014								X				X			
Chen B.; Wang L.; Yu S.; Wan J.; Xia X.	2024					X						X				X
Busogi M.; Ransikarbum K.; Oh Y.G.; Kim N.	2017	X	X			X		X								X
Zhou B.; Zha W.; Ye L.; He Z.	2022	X			X		X					X	X			X
Wang K.-J.; Eunike A.; Kurniawan I.; Ardi R.; Chiu J.-M.	2023					X		X		X		X		X		
Liu Q.; Song J.; Lv J.; Tang O.; Zhang Z.	2022	X	X						X				X	X		
Anel J.I.; Català P.; Serra M.; Domenech B.	2022	X	X					X	X				X			
Mura M.D.; Dini G.	2023							X	X				X	X		
Morariu C.; Morariu O.; Borangiu T.	2014					X				X			X			
Tiacci L.; Mimmi M.	2018	X	X					X	X	X		X	X	X		
Jiang Y.; Wang D.; Xia W.; Li W.	2022					X		X	X			X	X			
Nishi T.; Kurakado H.; Liu Z.	2024									X		X	X			
Guo Y.; Zhang W.; Qin Q.; Chen K.; Wei Y.	2023	X	X			X		X	X				X	X		X
Hashemi-Petroodi S.E.; Thevenin S.; Kovalev S.; Dolgui A.	2020	X			X				X		X					
Fisel J.; Lanza G.	2016	X			X			X	X		X					
Alghazi A.; Kurz M.E.	2018	X	X					X			X					
Wang L.; Liu H.; Xia M.; Wang Y.; Li M.	2024	X			X					X						X
Oesterle J.; Bauernhansl T.; Amodeo L.	2016							X	X				X	X		
Lopes T.C.; Brauner N.; Magalhães L.	2022								X		X					
Hashemi-Petroodi S.E.; Thevenin S.; Dolgui A.	2022	X		X				X			X					
Meaghani Y.; Hashemi-Petroodi S.E.; Thevenin S.; Dolgui A.	2024	X		X				X			X					
Razali M.M.; Ab Rashid M.F.F.; Make M.R.A.	2016								X		X			X		
Basán N.P.; Achkar V.G.; Méndez C.A.; García-Del-Valle A.	2017	X	X							X	X	X				
Hashemi-Petroodi S.E.; Thevenin S.; Dolgui A.	2024	X			X		X	X	X	X	X	X	X			X
Hashemi-Petroodi S.E.; Thevenin S.; Kovalev S.; Dolgui A.	2022							X	X		X					
Ali I.; Ghanem N.; Fors M.N.	2020								X		X					
Gultekin H.; Tula A.; Selim Akturk M.	2016	X		X				X	X		X					
Wu Y.; Zhao X.; Xu Y.; Chen Y.	2020	X			X	X		X	X				X	X		
Ljopis J.; Lacasa A.; García E.; Montés N.; Hilarío L.; Vizcaino J.; Vilar C.; Vilar J.; Sánchez L.; Latorre J.C.	2022								X			X				
Zhang X.; Ming X.; Bao Y.	2022	X			X			X	X				X			
Papakostas N.; Pintzos G.; Giannoulis C.; Nikolakis N.; Chrysosouris G.	2014	X		X				X	X				X	X		
Yang Z.; Xu W.; Wong P.-K.; Wang X.	2015	X			X	X		X		X				X		X
Coelho F.; Macedo R.; Relvas S.; Barbosa-Póvoa A.	2022								X			X				
Oesterle J.; Amodeo L.	2014							X	X				X	X		
Sadeghi P.; Rebelo R.D.; Soeiro Ferreira J.	2017								X				X			
Sadeghi P.; Rebelo R.D.; Ferreira J.S.	2018								X			X	X			
Alhomaiddi E.; Askin R.G.	2024							X	X					X		
Qin Y.	2023							X	X			X				
Caputo A.C.; Pelagagge P.M.; Salini P.	2015	X		X			X	X			X					
Law E.K.W.; Yung W.K.C.	2017	X			X	X		X	X			X				X

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Chen J.C.; Chen Y.-Y.; Chen T.-L.; Kuo Y.-H.	2019					x	x	x		x	x
Wang L.; Liu H.; Xia M.; Wang Y.; Li M.	2023	x		x		x			x		x
Caputo A.C.; Pelagagge P.M.; Salini P.	2015	x		x		x	x			x	
Law E.K.W.; Yung W.K.C.	2017	x		x		x	x			x	x
Chen J.C.; Chen Y.-Y.; Chen T.-L.; Kuo Y.-H.	2019					x	x	x		x	x
Wang L.; Liu H.; Xia M.; Wang Y.; Li M.	2023	x		x		x			x		x
Rane A.B.; Sunnapwar V.K.; Chari N.R.; Sharma M.R.; Jorapur V.S.	2017					x				x	
Colledani M.; Ratti A.; Senanayake C.	2015					x					x
Zhao C.; Li J.	2014	x		x		x					x
Mukalay T.A.	2020	x		x		x		x		x	
Huang J.; Chang Q.; Arinez J.	2020	x		x				x		x	
Caputo A.C.; Pelagagge P.M.; Salini P.	2015					x	x			x	
Yelles-Chaouche A.R.; Gurevsky E.; Brahimi N.; Dolgui A.	2024					x	x			x	
Koskinen J.; Raduly-Baka C.; Johnsson M.; Nevalainen O.S.	2020						x	x		x	
Uzunosmanoglu M.; Raa B.; Limère V.; De Cock A.; Singh Y.; Lopez A.J.; Gautama S.; Cottyn J.	2021	x		x		x	x	x		x	
Keshvarparast A.; Katiraei N.; Pirayesh A.; Battaia O.; Berti N.	2023					x	x			x	
Stief P.; Burgat G.; Pour- Massahian-Tafti M.; Dantan J.-Y.; Siadat A.	2023					x		x	x		x
Pereira J.	2018					x	x			x	
Manzini M.; Demeulemeester E.; Urgo M.	2022	x		x				x			x

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