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A conceptual framework for the operations planning of the textile supply chains: Insights for sustainable and smart planning in uncertain and dynamic contexts

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ABSTRACT

Recent practices in textile supply chains (SC) show a growing concern for sustainability not only in its economic dimension, but fundamentally in its environmental and social ones. One of the key management processes that affect sustainability is the SC operations planning since its fundamental role in achieving a balance between supply and demand in a sustainable manner. Moreover, in an uncertain and dynamic environment such as the textile sector, it is necessary to provide a certain learning capability to the operations planning techniques used to increase the speed and quality of response of the textile SC to unexpected situations. In this context, mathematical programming models, heuristics and artificial intelligence techniques have proven their validity to achieve sustainable, robust and smart supply chains. Despite their potential, neither a conceptual framework (CF) nor a literature review have been detected to support the development and study of such models in the textile supply chain operations planning. In view of these gaps, this paper proposes a CF for supporting the sustainable and smart operations planning of the textile supply chains in a dynamic and uncertain context based on a set of dimensions, categories and elements that reflect the specific characteristics of the textile sector. Firstly, a tentative CF is predefined based on other generic works on SC operations planning in uncertain context and the own authors' knowledge. Secondly, a structured literature review based on this CF has been made resulting, at the same time, in the updating of some of its dimensions, categories and elements to reflect some textile specific characteristics. Consequently, the CF is not only predefined but also logically derived from the literature analysis. The results of the literature review show that there is a great opportunity to contribute to making textile supply chains more sustainable, smart, flexible, robust and resilient in dynamic and uncertain environments.

1. Introduction

Industry of fashion and apparel (F&A) is one of the largest economies in some regions such as Asia Pacific, Europe and North America with an important projected sales growth in the next years (Giri et al., 2019) becoming its efficient management in a relevant issue. However, textile supply chains (SCs) present inherent characteristics that complicates its management. Indeed, textile industry is characterized by international trade, making these SCs to be globally dispersed. This aspect rises pressure in global markets to strengthen environmental and labor management (Hoque et al., 2021). This industry is also one of the largest waste producers because of problems like overproduction, product returns and short life cycle of products. Consequently, textile SCs are obliged to adopt sustainable production practices to minimize waste and facilitate its management (Giri et al., 2019). To achieve this goal, the right coordination of supply and demand in a sustainable manner becomes crucial, being one of the most relevant processes the so-called supply chain operations planning (SCOP). SCOP tries to the release of materials and resources in such a way that customer service constraints are met in the most efficient way for the SC (de Kok & Fransoo, 2003).

Typically, existing operating planning models do not take into consideration all the distinctive characteristics of companies of this

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sector (Rabbani et al., 2016). This is mainly due to the different sources of uncertainty that these companies have to deal with, such as, production, operating and transport resources capacity, set-up costs, customer demand, customer preferences as well as purchase and sale prices of manufactured goods (Demirel et al., 2018). In an environment as uncertain and turbulent as that of this sector, it is essential to address the dynamic nature of the processes in order to achieve an adaptive system to changes in the environment, unexpected events and differences between plans and reality, often as a consequence of uncertainty. These aspects oblige to move to the synchronized SC operations planning in which a constant flow of data allow to improve the precision and agility of operations planning to match the customers' demand (Rodríguez et al., 2020). An intensive use of on-line data facilitates real-time decision-making that could require automated planning attainable through the incorporation of learning capabilities making it smarter and higher responsiveness.

Therefore, in the uncertain and turbulent environment of textile SCs is of vital importance that operations planning adapts dynamically and intelligently to the changes that may occur, and the outcomes from what has been learned (i.e., resulting adaptations) contribute to the improvement of this industry-type competitiveness through a dynamic operations planning.

This brings one to the concept of smart or intelligent SCOP which should make advantage of the proliferation of Industry 4.0 (I4.0) technologies such as internet of things (IoT), cloud computing, digital infrastructure, big data analytics (BDA), artificial intelligence (AI) and optimization to (Oluyisola et al., 2021): enable the reduction of uncertainty (demand, process times, available capacity, …) by using real-time SC data and predicting system parameter values; allow dynamic replanning; capture the experience and knowledge of the employees and the planners over time and increase the SC agility. Besides, it is essential to make use of the potential offered by I4.0 and its associated digital technologies in relation to the large amount of real-time data availability. Indeed, in situations of large data volumes, AI techniques provide capabilities for (Hariri et al., 2019; Min, 2010): integrate and transform data, real-time decision-making, automate decision-making and incorporate learning capabilities. When this AI is combined with the new technologies identify the term AI 2.0 (Cheng & Yu, 2019) which includes Cloud Computing, BDA, IoT, Natural Processing Learning, Machine learning, etc. Therefore, a proper analysis of this large volume of data through AI techniques can be key to improve the sustainability of companies in the textile industry since they allow a more accurate monitoring of the process by immediately detecting unexpected events and risks that require re-planning. This re-planning, either by period or by event, should make use of the learning and optimization potential of AI and mathematical programming models. Through the learning and optimization capability of these techniques, sustainable and smart operations planning in a dynamic and uncertain context will be possible.

The benefits offered by all I4.0 technologies are widely developing in other industries such as port and maritime, plastics, healthcare, among others, where they have progressed to more advanced levels than the textile industry (Seçkin et al., 2019; de la Peña Zarzuelo et al., 2020; Echchakoui & Barka, 2020; Aceto et al., 2020). According to Yildirim et al. (2018), when technological and informatics advances are integrated in the textile industry, it will increase efficiency generating higher productivity, lower costs, and shorter and more profitable processes. Therefore, the application of AI and optimization techniques, such as mathematical programming models, in the I4.0 context will allow a great reduction in operational inefficiencies, ensuring on-time delivery of finished products, significantly boosting the textile industry efficiency, sustainability, robustness and resilience (Rodríguez et al., 2020).

Notwithstanding the foregoing and despite the main role of AI techniques and optimization models to implement smart or intelligent operations planning decisions, up to our knowledge there is any Conceptual Framework (CF) that assist in the task of developing this type of solutions in the textile industry. We have not also found any systematic literature review on AI and optimization techniques applications to the textile SCOP making advantage of I4.0.

Instead, we have found research proposing either CF or performing systematic literature reviews on operations planning in the textile industry but none from the AI or optimization models perspective. There are works dealing in a general way with the production and operations planning in the apparel and textile industry under different scenarios (Burnes & Towers, 2016; Fister et al., 2010; Grieco et al., 2017; Leung et al., 2003; Lin et al., 2019; Puasakul & Chaovalitwongse, 2014; Wang et al., 2014; Lorente-Leyva et al., 2020; Lorente-Leyva et al., 2021) as well as specific applications of different methods for their optimization (Ardjmand et al., 2016; Bakar et al., 2017; Felfel et al., 2016; Golmohammadi, 2015; Kumar et al., 2018; Leung et al., 2006, 2007; M'Hallah & Bouziri, 2016; Perić et al., 2018; Ren et al., 2017).

Some literature reviews exist on AI and optimization techniques for solving different problems in the textile industry but not centered on the SCOP as this paper. Along these lines, Guo et al. (2011) revised the applications on AI in the apparel industry for a wider perspective focusing on four areas: apparel design, apparel manufacturing (including the production planning and control tasks), apparel retailing and apparel supply chain management. Although the production planning and control tasks and the SC management are strongly related to the SCOP process under study, the first one is focused on one single facility at the more operative level of scheduling and balancing. The second one mainly addressed some separate decision-making problems in apparel supply chains, such as replenishment and inventory management. However, they do not either model or optimize the apparel SC from a whole perspective. Ngai et al. (2014) perform a review on decision support and intelligent systems for the textile apparel SC in a general way. They classified the papers based on the stages in the supply chain (textile production, apparel manufacture and distribution/sales) and the decision support and intelligent system adopted (Expert system, Genetic algorithm, Artificial neural network, Knowledge-based system, Decision support system, Fuzzy-logic system and Hybrid). Giri et al. (2019) study the impact of AI in the fashion and apparel SC based on the following categorization: Applied AI class and algorithm, SC stage under study, Business perspective and Research gaps identified. As it can be observed, these reviews although related do not focus on the SCOP process that is the scope of this paper.

In the field of AI, Kobbacy and Vadera (2011) investigate the use of AI in operations management, with its ability to develop solutions, handle uncertainty, and perform optimization. In fact, numerous applications of AI for the operations planning of manufacturing companies exist (Giri et al., 2019; Hu et al., 2017; Cheng et al., 2018; Lin & Gen, 2018). There are also some revisions of AI and optimization techniques for the SCOP in general but not for the textile SCs. Along these lines, Burggraf et al. (2018) perform a review of the current status of AI applications in production management and research trends in this area in academia. Recently, Rodríguez et al. (2020) perform a revision of the existing literature reviews on the AI techniques that include some process related to the operations planning and the sector of application. As a conclusion of their revision, they state that the majority of the AI reviews are not focused on one specific sector, recognizing the utility that reviews on specific sectors can have for practitioners and researchers. Additionally, the objectives pursued by the AI techniques are not analyzed in these studies, even less from the three pillars of the sustainability. This paper covers these previous aspects.

The above analysis leads us to conclude that there is no CF for supporting the development of AI and mathematical programming models for the SCOP of textile industries considering their inherent characteristics, their uncertainty and the role of new I4.0 technologies. For achieving the above objective, it is necessary to: (1) identify the textile SCs characteristics, uncertainty sources, decisions as well as mathematical programming models and AI techniques that have been employed when planning the operations of textile SCs; (2) establish the state of the art based on the above aspects to assist users in developing such solutions and (3) detect existing gaps in the literature in order to improve existing solutions or define the new ones when required.

This paper aims to fill the literature gaps as regards the absence of a CF for the sustainable and smart operations planning of the textile SCs in a dynamic and uncertain context and the corresponding systematic literature review. The utility of the CF is manifold. It will allow the characterization of the textile SCOP problems and use it as a reference model to develop the optimization or AI techniques. Besides, the classification of existing research based on the CF dimensions during the literature review, will support the development of these models by consulting existing works with the same or similar characteristic to be modelled. Finally, the structured literature review provides researchers with underexplored research areas.

The rest of the paper is structured as follows: Section 2 presents the research methodology followed in this paper. Section 3 describes the process of searching, delimiting and collecting the material and Section 4 presents the descriptive analysis of the material, evaluation and formal visualization. Section 5 details the CF proposal for the sustainable and smart textile SCOP operations planning that consider the inherent characteristics of the textile industry and their uncertainty. Section 6 reports the analysis of a structured literature review based on the CF dimensions. Finally, conclusions and future prospects in the research domain are presented in Section 7.

2. Research methodology

The research methodology followed in this paper, combines those proposed by Seuring and Müller (2008) and Esteso et al. (2018). On one hand, Seuring and Müller (2008) derives a CF from a literature review following a four step methodology: 1) Material collection, 2) Descriptive Analysis, 3) Category Selection and 4) Material evaluation. On the other hand, Esteso et al. (2018) derives and validates their CF by means two phases. In the first phase a CF is proposed, meanwhile in the second phase, the CF dimensions are used as the taxonomy to perform a structured literature review that validates the proposed CF and allows to identify literature research gaps.

The resulting methodology of combining the two previous ones and followed in this paper can be consulted in Fig. 1. As it can be seen it consists of five steps: **1) Material collection**, during which the material to be collected is defined and delimited; **2) Bibliographic data processing and visualization**, that consists in a descriptive analysis where formal aspects of the material are assessed (e.g., the number of publications per year) by adding a more update visualization perspectives of the data, **3) Tentative CF definition** by means the selection of the structural dimensions, categories and elements. It is important to note that the first tentative CF proposal was based on previous general studies consulted in similar SC topics and the own authors' knowledge. This starting point presents the advantage of not limiting to the existing literature in the sector, providing a wider perspective to detect gaps. Additionally, in order to avoid the possibility of missing specific potential dimensions, categories or elements of the textile SCs, this first CF preliminary version has been updated and modified during the revision of papers in the textile sector. **4) Structured literature review** including the material analysis and evaluation according to the structural dimensions, selected categories and elements of the current tentative CF and **5) Final CF proposal,** representing the last version of the tentative CF once the **Final Structured Literature Review** has been obtained. It is important to note that the Steps 3 and 4 are iterative in the sense that during the revision process original structural dimensions, categories and their elements have been adapted as a consequence of the literature analysis made on the textile sector because some of them are perceived missing or not properly defined. Consequently, the dimensions, categories and their elements are not only predefined but also logically derived from the literature analysis. This means that a feedback can exist from Step 4 to 3 in such a way that the evaluation of specific research can require the modification of the tentative CF proposal in order to adapt it to the textile sector. This mixed procedure from the generic perspective to the specific textile one and vice-versa, has the advantage to provide a wider perspective of SCOP not limited to the textile sector but also taking it into account. This has allowed us to find out understudied areas and research gaps for devising future research lines. Next sections implement this research methodology.

3. Material collection

Following the above research methodology, we proceed with the first step consisting in the delimitation and compilation of the material whose detail can be consulted in Fig. 2. The literature search about SCOP optimization and AI techniques in the textile industry was performed by considering scientific articles in Web of Science (WoS) and Scopus, the databases that currently contain the largest indexing services (Mongeon & Paul-Hus, 2016), and the largest collection of peer-reviewed scientific literature. The time window is delimited until September 2023. The

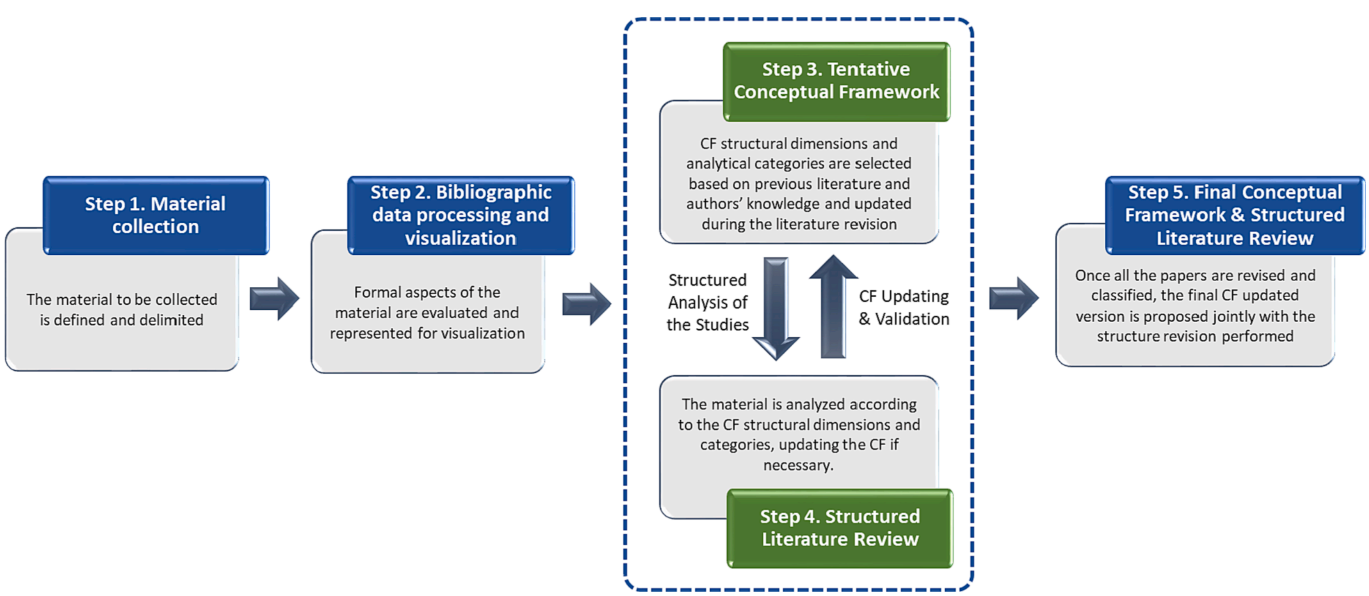

Fig. 1. Research methodology (adapted from Seuring and Müller (2008) and Esteso et al. (2018)).

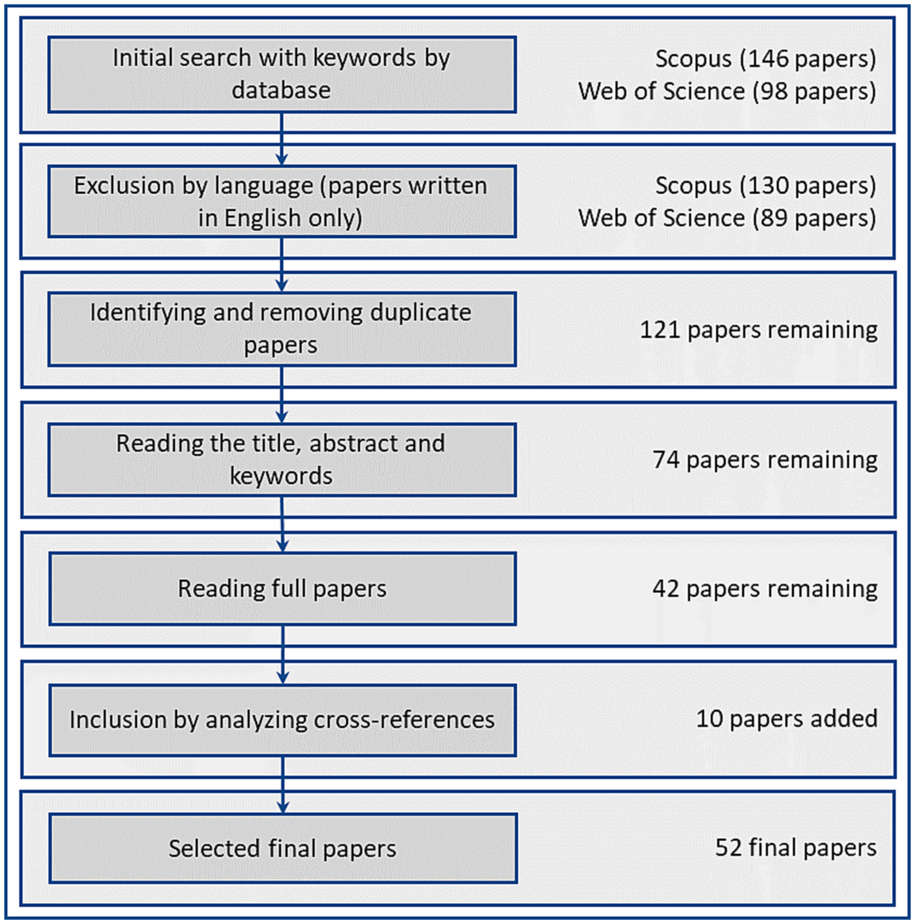

Fig. 2. Document search and collection process.

employed keywords were the following focused on the fields Title-Abstract-Keywords:

- TITLE-ABS-KEY ("operations planning" OR "production planning" OR "supply chain planning" OR "programming" OR "network planning" OR "sequencing" OR "distributing" OR "last mile")
- AND ("industry 4.0" OR "artificial intelligence" OR "machine learning" OR "fuzzy logic" OR "data mining" OR "expert systems" OR "big data" OR "smart" OR "intelligent" OR "mathematical programming" OR "linear programming" OR "mixed integer" OR "multi-objective" OR "optimization" OR "heuristics" OR "metaheuristics" OR "matheuristic" OR "hyper-heuristic")
- AND ("textile" OR "apparel" OR "garment" OR "clothing" OR "fashion")

An exhaustive search of related works has been carried out, considering those in which important contributions and applications for SCOP in the textile industry have been included, compared and developed. Based on the analysis of the initial search for information through the chain of consultation described above, a manual filtering of the documents is carried out to determine which are the most relevant for the study and to guarantee the quality of the review process. A set of inclusion criteria were defined where studies must be peer-reviewed and written in English.

As detailed in Fig. 2 the search process, where initially a total of 146 papers in Scopus and 98 papers in Web of Science referring to the topic under study are obtained. Considering only the documents written in English, 130 papers were obtained from Scopus and 89 from Web of Science. Excluding duplicates, a total of 121 documents were maintained. To discard those that are not related to the topic under study, a careful reading of the title, abstract and keywords fields has been carried out, remaining 74 papers. From the initial 74 papers, those that did not neither directly model the operations planning, nor develop solution strategies, nor present the validation of the proposed solutions, were discarded. Similarly, those only consisting in summaries at length, without specific results in the study area under review, were also removed from this study, remaining the last 42 papers. From the cross-reference consultation we include 10 papers that present important findings and applications. Thus, the number of final papers included in this paper is 52.

4. Bibliographic data processing and visualization

During this second step a descriptive analysis of the material is performed for a formal evaluation and visualization. Table 1 presents the ranking by literature source of publication of the selected final articles in alphabetical order. As it can be observed the publications are very dispersed not existing journals with a high concentration of papers in this topic. The highest number of published articles is four in the journal Computers and Industrial Engineering. Other journals in industrial engineering, operations research, intelligent manufacturing, expert systems applications, and management science top the list. Engineering and technology, industry applications, artificial and computational intelligence, and manufacturing journals account for the largest number of publications which consist of only two publications. The rest present only one publication. Of the 52 articles analyzed, 43 sources were identified, 86 % of which correspond to scientific journals and 14 % to international conferences.

The related sources cover a time window of 35 years (Fig. 3). It can be appreciated a discontinuous and irregular frequency of publication,

Table 1
Publications by source.

Source	Authors	Papers	Percentage
Annals of Operations Research	Felfel et al. (2018)	1	1.92 %
Advances in Intelligent Systems and Computing	Guo et al. (2019)	1	1.92 %
Applied Soft Computing Journal	Darvishi et al. (2020)	1	1.92 %
Applied Sciences	Ferro et al. (2021)	1	1.92 %
Computers and Industrial Engineering	Felfel et al. (2016), Tsao et al. (2020), Yaghin (2020), Zhang et al. (2021)	4	7.69 %
Computers in Industry	Karacapilidi and Pappis (1996), Wong et al. (2000)	2	3.85 %
Computers, Materials and Continua	Wang et al. (2022)	1	1.92 %
Discrete Dynamics in Nature and Society	Wang et al. (2018)	1	1.92 %
Energies	Tsai (2018)	1	1.92 %
Engineering Applications of Artificial Intelligence	Yaghin et al. (2020)	1	1.92 %
European Journal of Industrial Engineering	Hung et al. (2014)	1	1.92 %
Expert Systems with Applications	Ford and Rager (1995)	1	1.92 %
Fibres And Textiles in Eastern Europe	Campo et al. (2018), Ünal and Yüksel (2020)	2	3.85 %
Fuzzy Optimization and Decision Making	Ertuğrul and Tuş (2007)	1	1.92 %
Human Factors and Ergonomics in Manufacturing	Shao et al. (2014)	1	1.92 %
IEEE Access	Chong et al. (2022)	1	1.92 %
IEEE SSCI 2011: Symposium Series on Computational Intelligence	Mok (2011)	1	1.92 %
IFAC Proceedings Volumes	Sengupta et al. (2008)	1	1.92 %
IMA Journal of Management Mathematics	Safra et al. (2019)	1	1.92 %
International Journal for Quality Research	Tesfaye et al. (2016)	1	1.92 %
International Journal of Advanced Manufacturing Technology	Xu et al. (2020)	1	1.92 %
International Journal of Clothing Science and Technology	Tabucanon and Estraza (1989), Yaghin and Sarlak (2022)	2	3.85 %
International Journal of Mathematics in Operational Research	Woubante et al. (2019)	1	1.92 %
International Journal of Production Economics	de Toni and Meneghetti (2000)	1	1.92 %
International Journal of Services and Operations Management	Amuthakkannan et al. (2010), Celikbilek et al. (2016)	2	3.85 %
International Journal of Supply and Operations Management	Ben Abid et al. (2022)	1	1.92 %
International Journal of Simulation Modelling	Zhang (2015)	1	1.92 %
International Review on Modelling and Simulations	Vasant et al. (2011)	1	1.92 %
IOP Conference Series: Materials Science and Engineering	Khannan et al. (2018)	1	1.92 %
Journal of Applied Mathematics and Informatics	Suraiya and Hasan (2023)	1	1.92 %
Journal of Intelligent Manufacturing	Wong et al. (2006), Mok et al. (2013)	2	3.85 %
Journal of the Operational Research Society	Karabuk (2008)	1	1.92 %
Journal of the Textile Institute	Wong and Chan (2001)	1	1.92 %
Lecture Notes in Computer Science	Lorente-Leyva et al. (2019)	1	1.92 %
Management Science	Degraeve and Vandebroek (1998)	1	1.92 %
Mathematics	Wang et al. (2021)	1	1.92 %
Mathematical Problems in Engineering	Ait-Alla et al. (2014), Ben Abid et al. (2020)	2	3.85 %
Omega	Weskamp et al. (2019)	1	1.92 %
Operations Research and Decisions	Malik et al. (2022)	1	1.92 %
Proceedings of the IEEE Conference on Decision and Control	Tomastik et al. (1995)	1	1.92 %
Sustainability (Switzerland)	Sardar et al. (2016)	1	1.92 %
Tekstil ve Konfeksiyon	Puzovic et al. (2018)	1	1.92 %
Uncertain Supply Chain Management	Rabbani et al. (2016)	1	1.92 %
Total		52	100 %

corresponding around the 70 % of the publications to the last 10 years. This fact indicates a greater interest in the subject and a remarkable growth in the development of operations planning optimization and AI research in the textile industry.

The VOSviewer tool (van Eck & Waltman, 2010) is used for the construction and visualization of bibliometric networks (van Eck & Waltman, 2014). For this purpose, the analysis of the scientific production behavior obtained from the quantitative and qualitative point of view is developed. The keyword analysis obtained from the different references by means of a co-occurrence map can be consulted in Fig. 4. This visualization shows which keywords have been the most important in the selected publications and what is the co-occurrence relationship: the greater the distance between them, the smaller the relationship. The colors represent the clusters containing the keywords with the greatest proportion of co-occurrence. The size of the clusters represents the frequency of the keywords that have been used in the literature under analysis and each cluster contains the co-occurrence ratio. Therefore, it has been determined that the highest frequency is represented by the keywords that visualize the largest clusters, such as production control, production planning and textile industry, followed by optimization and mathematical programming methods. SC analysis and the application of metaheuristic methods, such as genetic algorithms, are among the most identifiable words of the developed works. Similarly, the models, techniques and tools for the solutions include the development of linear, nonlinear and integer programming models as well as the application of fuzzy sets and AI techniques. On the other hand, it has been identified that keywords such as industry 4.0 has been little used and those related to sustainability, intelligent, smart, resilience and robust do not appear in the analysis and visualization developed.

5. Conceptual framework

The description of the proposed CF is made in this section. The CF purpose is to serve as a guide tool to develop optimization methods (mathematical models and AI techniques) to achieve sustainable and smart textile SC operations planning in dynamic and uncertain context, as well as to perform a structured review of existing models. The proposed CF intends to cover not only the inherent and particular characteristics affecting the operations planning of textile SCs but also those ones relevant although common to other SCs. All this, considering the opportunities provided by the I4.0 context.

As explained in the previous section, firstly, a tentative CF has been

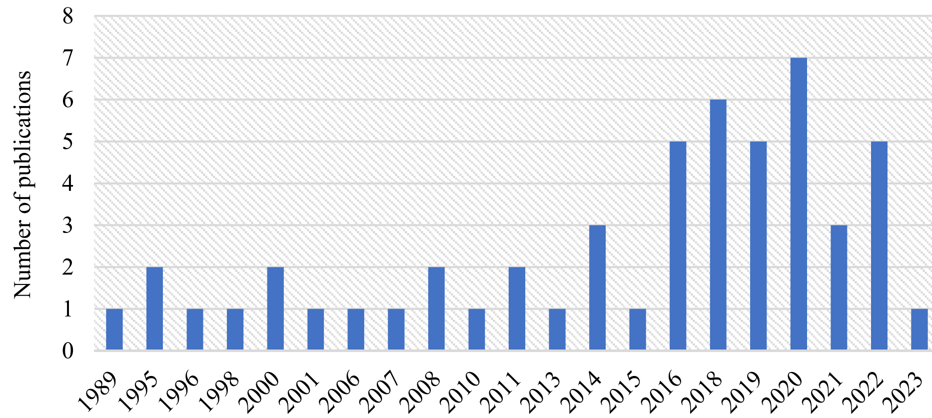

Fig. 3. Publications per year.

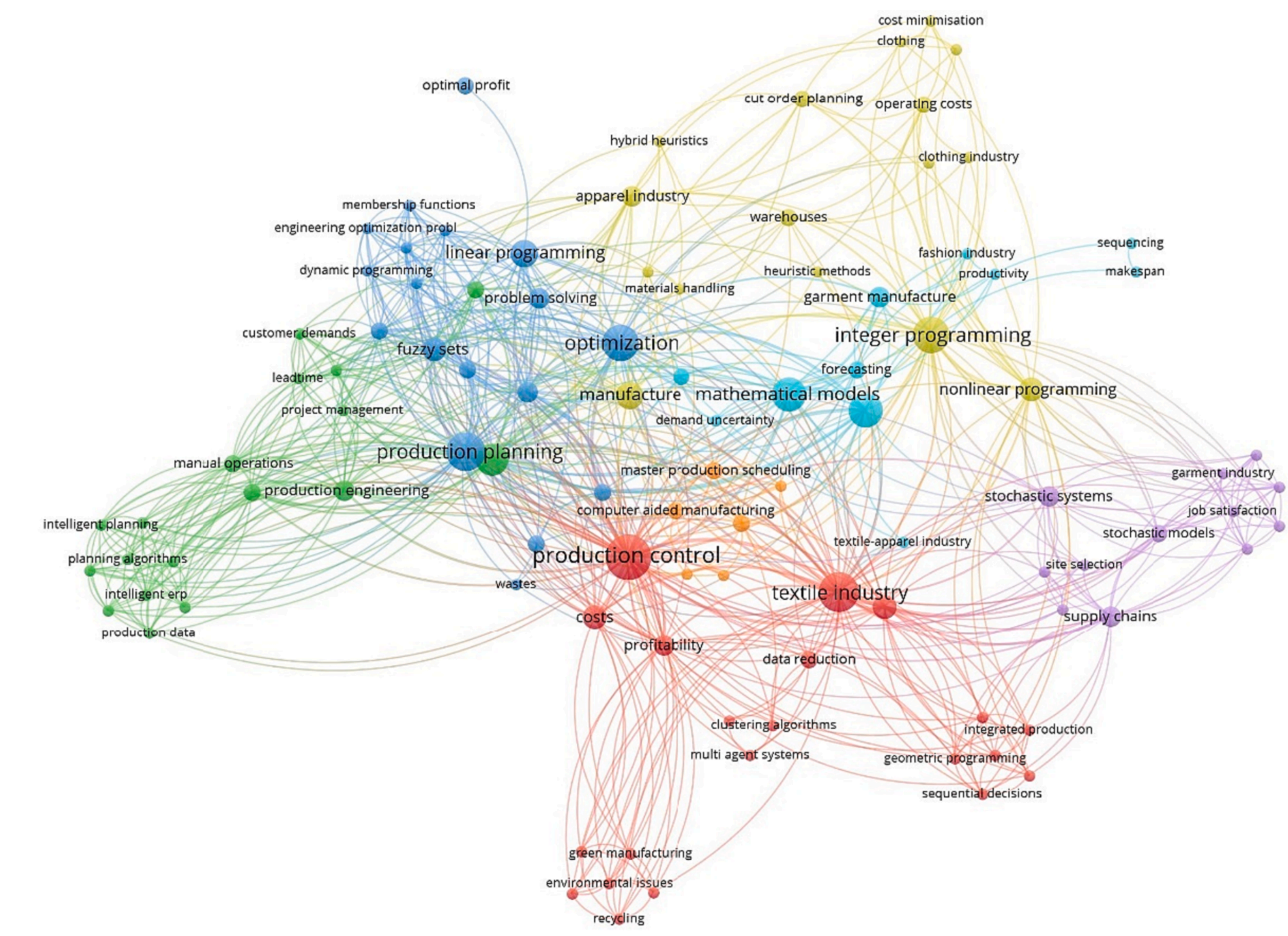

Fig. 4. Network visualization and keyword co-occurrences.

proposed based on previous reviews and other CF for SC operations planning in an uncertain context from which different dimensions and categories have been defined. These works, conveniently cited during the description of the CF dimensions and categories, have been those of Mula et al. (2010), Grillo et al. (2016), Esteso et al. (2018) and Mundi et al. (2019). The final CF derived can be considered as a combination of some dimensions and categories of these previous works plus new ones included for the purpose of this work based on authors' knowledge, for instance, to reflect the smart and dynamism features required to adapt planning to the changing environment. Besides, each category is divided into a series of elements that are specifically derived from the textile sector not having been previously considered in previous CF and literature reviews.

The CF proposed is divided into five dimensions (Fig. 5): Environment, Managerial Characteristics, Uncertainty Characterization, Model Characteristics and Resolution Approach. Each dimension is integrated by several categories composed in turn by different elements gathering specific characteristics of the subject under study. Existing relationships

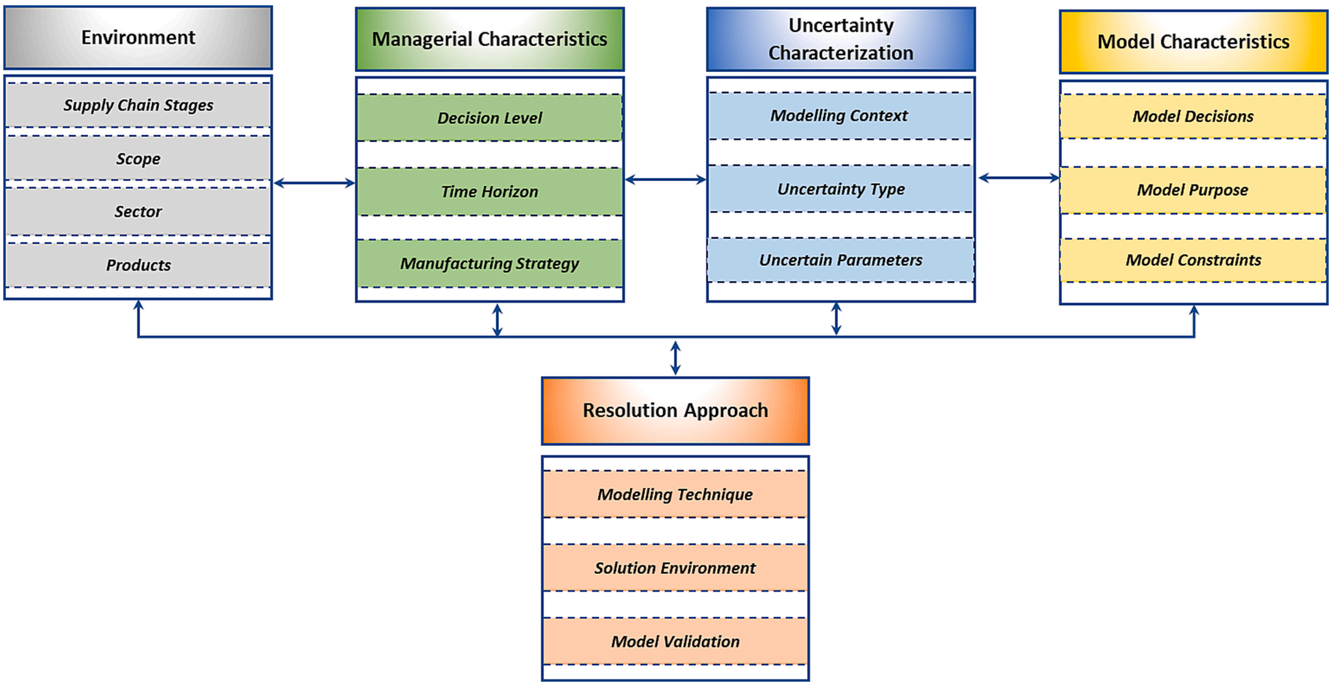

Fig. 5. Conceptual framework for the analysis.

among the different dimensions on the CF are represented by bidirectional arrows in Fig. 5. Paragraphs below describe in detail all the dimensions and their relationships.

5.1. Environment

Although sharing similar characteristics, each textile SC operates in a specific environment that should be considered when planning its operation. Therefore, it is relevant to identify the following categories: Supply Chain Stages, Scope, Sector and Products.

5.1.1. Supply chain stages

The operations planning of SCs requires more or less coordination effort depending on the number of stages involved. Therefore, to identify the stages of the SC for which planning is carried out becomes of relevance. Following the proposal of Grillo et al. (2016), four main categories are distinguished:

- Supply (Sup)
- Manufacturing (Man)
- Storage and Distribution (SD)
- Sales (Sal)

5.1.2. Scope

The global dispersion of textile SCs can lead to not negligible implications for the operations planning as regards supply, transport means, currency aspects, policies, standards and rules to be respected by different nodes. Therefore, it would be necessary to take into account if the SCs nodes of each stage are located in the same or different regions or countries. Consequently, a distinction is made among:

- Local scope: when nodes of all stages are located in the same locality/region.
- National scope: when there are nodes located in different locations within the same country.
- International scope: when there are nodes in different locations in different countries.

The scope can be relevant since policies, laws, regulations and also different currencies may require their explicit modelling.

5.1.3. Sector

The textile industry is composed by long and complex industrial chains. It can be considered a fragmented and heterogeneous sector in which small and medium-sized companies predominate (Hasanbeigi & Price, 2012) and where demand originates mainly in the following subsectors:

- Apparel: it refers to the manufacture of garments, clothing, fashion apparel, yarn products, fabrics, synthetic fibers, etc.
- Home textiles: it refers to home textile products, sheets, pillowcases, comforters.
- Industrial applications: it makes reference to textile products for industrial use, high performance fibers, resistant to high temperatures and chemicals.

It is important to note that the same company/SC may be associated with more than one of the aforementioned subsectors, and even with other related sectors, such as the leather or footwear industry.

5.1.4. Products

The complexity of the operations planning process can be affected by the quantity and characteristics of the products to be managed. In order to characterize these aspects, the following sub-dimensions are defined inspired in Esteso et al. (2018) but referring to the obsolescence instead of the perishability:

- Number of products: it refers to the products manufactured and distributed that are taken into account in the planning process, whether it is a single product or multiple (e.g., customized and single-configuration products, various types of products, product families, etc.).
- Obsolescence: it refers to trendy or fashion products whose value/utility decreases over the planning horizon, which may force their price to be lowered to sell them. This has implications for modelling, for instance, time-dependent pricing and limited time in stock.

5.2. Managerial characteristics

The management characteristics include aspects related to the SC decision-making that will impact its operations planning.

5.2.1. Decision level

It concerns the level of the planning hierarchy at which decisions are made (Mula et al., 2010). Since we are analyzing the planning process, only models at the tactical (medium-term) and operational (short-term) levels will be considered that affect the detail of decision and their horizon.

5.2.2. Time horizon

It is the planning horizon that refers to the time interval over which our planning decisions are spread. It can be divided into several periods (multi-period) or a unique period (single-period) (Esteso et al., 2018). The number of periods into which the time horizon is divided determines the number of decision points. Therefore, the higher the number of periods, the greater the number of decisions to be made. This increases the problem complexity, but also provides decision-makers with greater the flexibility.

5.2.3. Manufacturing strategy

The location of the customer's order decoupling point (CODP) for each product-market is essential when planning the operations of any SC (Grillo et al., 2016). This is because the CODP separates the part of the SC driven by forecasts from that driven by the customer orders. Along the first part of the SC (upstream the CODP and at the CODP itself), manufacturing and operations are made based on forecasts being possible to held inventory. However, downstream the CODP no inventory exists since operations are only triggered when a firm customer order is received. Besides, the CODP location determines the manufacturing strategies (Grillo et al., 2016): Engineering-to-Order (ETO), Make-to-Order (MTO), Assemble-to-Order (ATO) and Make-to-Stock (MTS).

5.3. Uncertainty characterization

There are multiple sources of uncertainty affecting the textile operations planning process that are reflected mainly in its input data. To conveniently gather them, this dimension is focused on the characterization of the uncertainty present in the studied planning problem but not in the specific techniques used to model it, that are analyzed in the dimension "Resolution Approach". The reason is that the model technique applied will depend on the uncertain characterization adopted (see Section 5.5). As in Esteso et al. (2018), three general categories are considered in this dimension: Modelling Context, Uncertainty Type and Uncertain Parameters. At this point, it is important to highlight that the "Uncertain Parameters" category could have also been included in the dimension "Model Characteristics" since parameters, as the input information of a model, represent one of its main characteristics. Despite this, since uncertainty is one pillar of this research, we have opted to present "Uncertain parameters" as one category of "Uncertainty characterization" with the aim of providing an integrated analysis of uncertainty in the textile sector. This approach, although not being the only valid, is aligned with that adopted by other authors, such as Grillo et al. (2016), Esteso et al. (2018) and Mundi et al. (2019).

5.3.1. Modelling context

When deriving a model for the reality, it is possible to try to reflect the uncertainty of the environment or to assume that all relevant for the model is known with certainty and adopt some protective measures such as, for instance, the safety stock to protect against the demand uncertainty. Although all the operations planning contexts present some type of uncertainty, we will distinguish between:

- Deterministic Context: the input data of the model is considered to be known with certainty.
- Uncertain Context: when the uncertainty of some input data of the problem under study is included in the model.

5.3.2. Uncertain type

The aim of this category is to identify the approach adopted to include uncertainty into models (Esteso et al., 2018) in case the uncertain modelling context is selected. Related to this, different perspectives can be found in the literature. A widely recognized approach is that presented in Samson et al. (2009) that review the perspectives of uncertainty according to the degree of knowledge of the information classifying them into two types: epistemic and aleatory uncertainty. Uncertainty is considered aleatory when the possible consequences or outcomes of decisions are known, and it is possible to estimate their probability. Some examples are stochastic programming which is often used interchangeably (Oberkampf et al., 2004). On the contrary, in an environment of epistemic uncertainty, the possible consequences of decisions are not known, and it is therefore impossible to know the probability of their occurrence. Some approaches, such as fuzzy set theories, can be employed for modelling epistemic uncertainty (Esteso et al., 2018).

Another generalized categorization is found in Morteza and Kuan (2012) that distinguishes between Distribution-based approach (stochastic methods), Fuzzy-based approach (fuzzy programming) and Scenario-based approach (robust optimization). On its part, Borodin et al. (2016), consider three different formats to express uncertain data are identified (deterministic-based, probabilistic and possibilistic), not considering the Scenario-based approach of Morteza and Kuan (2012), but including the additional deterministic-based approach. A fusion of these approaches are adopted in this paper that cover a wider perspective on uncertainty and allow us to define some relationships with the "Resolution Approach" (see Section 5.4.2):

- **Deterministic-based (DB) approach:** uncertainties are defined by parameter domains in which they can vary, i.e. by intervals, also called grey numbers or crisp sets. The interval programming and grey programming are usually adopted to model them. Situations studied in these fields are neither deterministic nor totally unknown, but rather they are partially known (Borodin et al., 2016).
- **Probabilistic (PB):** uncertainties are described via probability distributions (i.e. known probabilistic measures), describing the likelihood of a certain event occurring. This format belongs to the previous aleatory uncertainty type in Samson et al. (2009). Most used modelling methods include stochastic programming and chance constrained.
- **Possibilistic (PS)**: uncertainties are represented by fuzzy elements/sets, describing the possibility or membership grade of whether a certain event can be plausible or believable. This is equivalent to the epistemic uncertainty type in Samson et al. (2009). Flexible and possibilistic programming are two well-known approaches to model ambiguity and vagueness under a fuzzy decision-making environment (Govindan & Cheng, 2018).
- **Scenario-based approach (SB),** in which several discrete scenarios with associated probability levels are used to describe the expected occurrence of particular outcomes (Morteza & Kuan, 2012) as in robust optimization.

It is important to note, that in the same model more than one format to represent different type of parameters can be used depending on the nature of data and the knowledge of information.

5.3.3. Uncertain parameters

There are multiple sources of uncertainty that can affect the textile sector, so that solutions to the SCOP problem can quickly become unfeasible in the implementation phase due to the uncertainties present

(Usuga Cadavid et al., 2020). In this category, the aim is to identify the uncertain parameters present in the textile sector. The following parameters have been identified: Demand; Sale Prices; Exchange Rate; Materials Availability; Costs (Transport, Processing, Operating); Times (Transport, Processing, Operating); Available Capacity (Transport, Processing, Operating) and Decision-maker Penalties.

5.4. Model characteristics

Once characterized the SC environment, the next step is to identify the characteristics of the planning decision level as regards three main categories: Decisions, Objective/s and Constraints (Esteso et al., 2018; Grillo et al., 2016; Mula et al., 2010; Mundi et al., 2019).

5.4.1. Model decisions

The model decision are the unknowns of the problem on which the planner can act. They are independent variables of the model. The solution technique adopted tries to find out their value in order to either optimize the model purpose or achieve a satisfactory value while respecting the existing constraints. The potential decisions to be made are strongly dependent on the problem addressed. For the problem under study, the following variables were identified: Supply Quantity (SQ); Transport Quantity (TQ); Transport Mode (TM); Transport Capacity Sizing (TCS); Production Quantity (PQ); Setups (Set); Inventory Level (Inv); Lot Sizing (LS); Allocation (Alloc); Sequencing (Seq); Outsourcing (Out); Labour Sizing (LB); Number of Shifts (NS); Overtime (Ove); Sales (Sal); Unmet Demand (UD); Backorder Quantity (BQ); Product Settlement (PS); Returns (Ret); Energy Consumption (EC); Waste (Was).

5.4.2. Model purpose

The solution quality depends on the objectives pursued, that can be single or multiple, being possible to maximize or minimize each one. In addition, these objectives can be related to the three dimensions of sustainability (economic, social and environmental) as pointed out by other works (Esteso et al., 2018). However, other aspects not previously identified in consulted works related to the dynamism of the system and its uncertainty (flexibility, robustness and resilience) are identified for the purpose of this work. The on-line data provided by I4.0 technologies jointly with the improvement of the processes control can be very useful in achieving these last objectives. Thus, the potential objectives pursued are classified into the next six categories followed by some examples:

- Economic: profits maximization or costs minimization;
- Social: maximization of customer satisfaction, maximization of service levels or employment maximization;
- Environmental: minimization of water pollution, gas emissions, wastes or energy use;
- Flexibility: maximize the capacity to manage and adapt to changing conditions in a timely and cost-effective manner, to react appropriately and adjust easily when an unforeseen event occurs (Stricker & Lanza, 2014; Santos Bernardes & Hanna, 2009; Seebacher & Winkler, 2015);
- Robustness: maximize the ability to tolerate changes or disturbances, stability (Gyulai et al., 2017; van Landeghem & Vanmaele, 2002);
- Resilience: maximize the ability of the system to recover from a disruption (Pettersen & Asbjørnslett, 2019) or maximize persistence, adaptability, learning ability and agility (Kusiak, 2019; Schmitt et al., 2017).

5.4.3. Model constraints

The potential solutions to be implemented in the textile SCs should be feasible, this means that it must comply with a series of limitations or constraints. Depending on the problem under study, constraints are of different nature. For the operations planning problem constraints usually establish limitations on available capacity of specific resources (Productive Capacity (PC); Transport Capacity (TC); Storage Capacity (SC); Workforce Capacity (WC)), unspecified resources (Aggregate Capacity Constraints (ACC)); availability of materials, raw material, intermediate or final products, (Materials Availability (MA)), balance equations on them (Material Balance Constraints (MBC)), equations related to the demand (Demand Satisfaction (DS); Service level (SL)), and policy constraints (International Constraints (IC); Contracts Constraints (CC); Company Policy Constraints (CPC)).

5.5. Resolution approach

The Resolution Approach aims to determine the type of model used to represent the problem under study and the solution method applied to obtain the value of the decision variables that optimize the objectives or achieve a satisfactory solution respecting all the constraints. It also includes the environment in which the model is used that will allow it to adapt more or less dynamically to changes in the environment, even learning from it. Last, it is possible to validate the model to solve a case study or a real case. More details about these categories are provided below.

5.5.1. Modelling technique

When characterizing the modelling and solution technique used, it is interesting to know: the number of objectives pursued, the model type applied to obtain the solution quality level and, the intelligent character desired of the solutions obtained.

- Number of Objectives:

It comprises the number of targets present in the models:

- Single-objective: when optimizing a unique objective function is the aim.
- Multi-objective: when more than one objective is considered to form part of the model.
  - Mathematical Programming Models

Formulating the SC operations planning problem with mathematical programming models provide the possibility of achieving the optimal solution, that is finding the decision variables which maximize or minimize one or multiple objective functions subject to different constraints (Shapiro, 1993).

Depending on the nature of the decision variables (continuous and/or integer), the linearity or not of the different mathematical functions (linear or non-linear), the method to optimize multiple objectives and the technique used to include uncertainty (if applicable) different methods can be distinguished. In this research the selected papers are analyzed based on the classification adaptation proposed by Mula et al. (2010) and Mundi et al. (2019) enriched with some uncertain modelling techniques to more precisely detect gaps in the literature:

- Linear Programming (LP): the model equations and constraints are linear and decision variables continuous.
- Integer Linear Programming (ILP): the relationships in the model are linear and the decision variables integer or binary.
- Mixed Integer Linear Programming (MILP): it belongs to the linear type model with all types of variables (continuous, integer and binary variables)
- Non-linear programming and mixed integer/integer nonlinear programming (NLP): the objective and/or constraints do not remain linear
- Multi-objective programming (MO) includes mathematical programming models with several and conflicting objective functions to be optimized. Different methods have been developed for solving this type of models that can be classified into two main categories (Collette & Siarry, 2008): aggregated (e.g. global criterion, weighted sum

method) and non-aggregated methods (e.g. multi-objective evolutionary algorithms) (Trisna et al., 2016). Aggregate methods unless non-aggregated ones, transform the multi-objective problem into single objective problem (Donoso & Fabregat, 2007). This is usually done by aggregating all the objectives in a weighted function, or simply transforming all but one of the objectives into constraints (Ngatchou et al., 2005).

- Stochastic Programming (SP): it is a distribution-based approach for modelling problems that involve uncertainty in random parameters with known probability distributions (Morteza & Kuan, 2012). Different types of stochastic problems exist, for some of which equivalent linear programming counterparts can be formulated such as: chance-constrained programming, that is applied when one or multiple constraints are not required to be always satisfied, but on the contrary they need to be held with some probability or reliability level, and stochastic programming problems without recourse or with recourse (a type of two-stage programming) (Borodin et al., 2016)
- Robust Optimization (RO). Unless SP, RO does not make specific assumptions on probability distributions of the uncertain parameters. RO represents the uncertain input parameters using the parametric bounds. Typically, the lower and upper limits of the parameters are exploited to determine the uncertainty sets, followed by the selection of representative scenarios from the uncertainty sets (Ehsan and Yang, 2019). It is based on the integration of goal programming formulation with scenario-based description of a problem (Morteza & Kuan, 2012). To formulate the robust optimization problem, it is necessary to define a set of scenarios for the data. For each scenario, a probability of occurrence is known and a set of realizations exist for some coefficients of the control constraints. The optimal solution of the mathematical program will be robust with respect to optimality if it remains "close" to optimal for any realization of the scenarios. The solution is also robust with respect to feasibility if it remains "almost" feasible for any realization of scenarios. Robust optimization, while not without limitations, has some advantages over stochastic linear programming and is more generally applicable (Mulvey et al., 1995).
- Interval Method (IM): As RO, the IM implies random parameters with no available information about their probability distribution. For the IM, the possible range of variation of any uncertain parameter is represented by the interval, i.e., only the upper and lower bounds of the parameter need to be known, and it is not necessary to know the exact probability distribution or the fuzzy membership function (Peng et al., 2020).
- Grey Programming (GR): In GR decision-making is neither deterministic nor totally unknown, but rather they are partially known. In GR models, uncertainty can be represented in parameters as a grey number. GR is different from IM: the main difference in GR and IM is the concept of grey parameter and interval parameter, respectively. A grey parameter is a parameter, which belongs to an interval, but the interval parameter is a set in the form of an interval (Nasseri et al., 2016).

- Heuristic Methods (HM)

It includes a series of methods by means of which solutions are obtained that are not necessarily optimum in acceptable times. The development of efficient methods to find satisfactory solutions to difficult problems, where the quality and speed of the solution obtained is of vital importance, are called heuristic methods (Martí & Reinelt, 2011). The speed of the solution procedure can become very relevant in uncertain and dynamic environments if the flexibility and resilience should be improved when planning SC operations.

- Artificial Intelligence (AI) Methods

These methods are defined as systems with intelligent behavior that have the ability to learn and adapt to changes to achieve specific objectives based on the analysis of the environment and interaction with it (Duan et al., 2019). Mok et al. (2013) shown that these methods can substantially improve the quality of operations planning. They have been applied to other processes in manufacturing leading to saving in operation costs of the textile industry (Tsao et al., 2020; Wong & Leung, 2008).

Indeed, since the beginning of AI in 1956, researchers from many disciplines contributed to build this field of knowledge. For this reason, AI must be understood from a multidisciplinary perspective (Rodríguez et al., 2020). The transverse character of the AI has led to the identification of different classifications of AI methods and different AI branches depending on their development discipline. Along these lines Giri et al. (2019) provide a detailed review of the application of AI in the fashion and apparel industry, its impact and importance in recent years. The classification of Giri et al. (2019) is taken as the basis of this work that has been extended considering the proposal of Rodríguez et al. (2020) that focus also on SC operations planning. Then, the most relevant branches considered for the purpose of this research are the following:

- Metaheuristic Methods (MM)
- Fuzzy Logic and Fuzzy Sets (FL&FS)
- Neural Networks (NN)
- Expert Systems (ES)
- Machine Learning (ML)
- Multi-Agent Systems (MAS)
- Hybrid Models (HYM)

5.5.2. Solution environment

The textile and apparel industry is characterized by high levels of demand uncertainty, short product life cycles, fast turnaround time, large product variety, and a volatile and complex SC structure (Li et al., 2016). It is therefore essential to understand how the proposed model adapts to the changing and dynamic environment in which the textile business operates. In order to characterize the solution context of the developed models, the following subcategories are proposed:

- Static: the model is solved only once during the entire planning horizon.
- Dynamic: the model is solved several times during the planning horizon. This re-planning can be performed periodically at predefined and usually fixed time intervals (re-planning by period), or it can be performed whenever a disruptive event occurs that produces a change in some input data that jeopardizes the validity (feasibility or optimality) of the previous plan requiring a new solution (re-planning by event).
- Smart: the term smart is used in planning when the experience of previous model runs is incorporated either in a real environment or through simulated training under various scenarios, real-time resource synchronization, data-driven, networking and resource sharing (Kusiak, 2019). Usuga Cadavid et al. (2020) refer to the term smart manufacturing as technological advances that value data to generate improvements in production. To incorporate previous knowledge can allow to implement better and more stable decisions against variations in the context more rapidly, improving the sustainability, robustness and resilience of the textile SC.

5.5.3. Model validation

To validate the proposed models, two approaches are distinguished (Esteso et al., 2018): Case Study and Real Case. The data used for validation in the case study are obtained by simulation and those of the real case are obtained from real-world companies.

5.6. Relationships among CF dimensions

The different CF dimensions cannot be considered independent since multiple relationships exist among them, their categories and elements. These relationships are represented by the arrows in Fig. 5, being the most relevant ones explained in the following.

As this regard, the environment dimension affects the managerial characteristics one and vice-versa, especially in the time horizon and manufacturing strategy. The reason for that is the more complex the SC (more SC stages, wider SC Scope and more products) the greater the suitability to not over extend the time horizon length in order to maintain a reasonable model size for being solved. On the other hand, the manufacturing strategy (CODP location) impact the possible SC stages to be considered, that for operations planning purposes are those located upstream the CODP and at the CODP itself.

To consider the uncertainty when modelling the problem under study will depend on the environment characteristics (scope, products, etc.) and the managerial ones (the longer the time horizon and the higher the decision level, the greater the presence of uncertainty and the necessity of modelling it). This relationship can be also understood in the opposite way, that is, the desired level of uncertainty to be assumed can modify the time horizon.

On the other hand, the uncertainty characterization can impact the model characteristics. The uncertainty type and the uncertain parameters considered could require the modification of the model purpose and/or constraints depending the modeling technique selected. Besides the Uncertainty Characterization and the Model Characteristics dimension consider the Environment and Managerial characteristics in the input information of the problem under study (number of products and stages and their associate data (parameters), the outputs (decisions to be made), the model purpose and the constraints (reflecting SC stages (physical configuration) and the products (number and their characteristics)). For instance, the decisions to be made depend on the decision level, the SC stages, the SC scope (local, national or international), the product characteristics and the time horizon. A huge volume of information, decision variables, and constraints can lead to reconsider the SC stages to be modelled, the scope, the time horizon or even the modelling context in order to adapt the model complexity. Finally, all the previous dimensions can impact on the resolution approach adopted. More complex SCs should select heuristic and meta-heuristic techniques rather than optimal ones. High presence of uncertainty, would imply different Uncertainty Types as well as more “Dynamic” and “Smarter” operations planning. Finally, the “Model Validation” should be performed based on the specific values of previous dimensions and categories.

6. Structured literature analysis based on the conceptual framework

In this section the selected research papers on the topic were systematically classified according to the CF dimensions and its categories. As pointed out in section “2. Research Methodology”, simultaneously with the literature revision, the CF has been updated and modified in order to better reflect inherent textile sector characteristics. This methodology has provided as a result not only the CF but also a structured literature review. Besides, this allows to know the current state of the art in this field and also to identify under investigated or unexplored aspects for further research. This structured literature analysis is organized in the following manner. First of all, the papers were classified in different tables with columns representing the possible values comprising each category integrating the different CF dimensions. Secondly, a global analysis made for all the categories composing each CF dimension is reflected in the corresponding Sections called “Findings”. Thirdly and finally, the global analysis considering all the dimensions is presented in the concluding section. It represents the last section of this research where the literature gaps and future research lines are devised.

6.1. Environment

The 52 papers selected where revised as regards the four categories integrating the environment dimension in Table 2 marking with a cross the characteristics covered by each paper.

6.1.1. Supply chain stages

From Table 2 it can be deduced that almost all the papers (96.2 %) considered the Manufacturing Stage when planning the operations of the textile SC, followed by the Storage and Distribution Stage (26.9 %) and Supply Stage (19.2 %). It is surprising that only one paper (1.9 %) takes into account the Sales Stage in an integrated SC of apparel production, marketing and retailing (Yaghin, 2020).

Most papers consider only one stage of the SC (65.4 %), mainly the Manufacturing one, except for a few papers addressing in isolated either the Storage and Distribution (Wang et al., 2018) or the Supply (Sardar et al., 2016) stages. On the other hand, only 25.0 % of the papers deal with the SC configurations of two stages such as, Supply-Manufacturing (de Toni & Meneghetti, 2000; Karabuk, 2008; Karacapilidis & Pappis, 1996; Tomastik et al., 1995), Manufacturing-Storage and Distribution (Ben Abid et al., 2020, 2022; Chong et al., 2022; Felfel et al., 2016; Guo et al., 2019; Safra et al., 2019; Weskamp et al., 2019; Zhang, 2015) or Manufacturing-Sales (Yaghin, 2020). Operations Planning for simultaneously three SC stages is just performed in 9.6 % of the analyzed research (Ait-Alla et al., 2014; Darvishi et al., 2020; Felfel et al., 2018; Yaghin & Sarlak, 2022; Yaghin et al., 2020) with the combination Supply - Manufacturing - Storage and Distribution. Finally, no paper considers the configuration of the four stages of the SC.

6.1.2. Scope

As regards the scope of the optimization and AI techniques developed, it can be observed (Table 2) that the majority of the SCs covered by the analyzed research present their nodes in stages located in the same region (55.8 %), followed by far for those located within the same country (26.9 %). Only the 19.2 % of the models addressed SCs with nodes situated internationally (Ait-Alla et al., 2014; Ben Abid et al., 2020, 2022; Chong et al., 2022; Darvishi et al., 2020; Safra et al., 2019; Sardar et al., 2016; Shao et al., 2014; Wang et al., 2021; Yaghin et al., 2020).

6.1.3. Sector

The vast majority of the research have been focused in the apparel sector (92.3 %), mainly garments (Tabucanon & Estraza, 1989; Degraeve & Vandebroek, 1998; Wong et al., 2000; Wong & Chan, 2001; Wong et al., 2006; Mok, 2011; Mok et al., 2013; Zhang, 2015; Wang et al., 2022; Suraiya & Hasan, 2023) and fashion products (Ait-Alla et al., 2014; Ben Abid et al., 2020; Sardar et al., 2016; Wang et al., 2018; Wong et al., 2006), while the 7.7 % of the papers deal with home textile products (Ertuğrul & Tuş, 2007; Sengupta et al., 2008; Vasant et al., 2011; Puzovic et al., 2018). No paper addresses the operations planning of products for industrial applications.

6.1.4. Products

In terms of the number of products, it is noteworthy that the planning process in textile industries address the multiple products (61.5 %) a little more than a single product (38.5 %). It is even more surprising that no work considers obsolescence, mainly for those that refer to fashion products, for which their value decreases with time.

6.1.5. Findings

The above analysis of environment dimension provides us with interesting information on the closeness to reality of the textile problems posed. From the analysis performed it can be stated that the vast majority of the problems modeled are very far to provide a coordinated operations plan for the whole textile SCs. This is supported by the fact that most of the papers contemplate only one SC stage, mainly the

Table 2
Environment and Managerial Characteristics.

Reference	Environment																	Managerial Caracteristiscs							
	Supply Chain Stages								Scope			Sector			Products			Decision Level		Time Horizon		Manufacturing Strategy			
	Sup	Man	SD	Sal	Number of Stages				Loc	Nat	Int	ACI	HT	IA	Number		Obs	Tactical	Operative	Single-period	Multi-period	ETO	MTO	ATO	MTS
					1	2	3	4							Sin	Mul									
Tabucanon and Estraza (1989)		X			X				X			X			X				X	X			X		
Ford and Rager (1995)		X			X					X		X			X			X		X			X		
Tomastik et al. (1995)	X	X				X			X			X			X			X		X					X
Karacapilidis and Pappis (1996)	X	X				X			X			X			X			X			X				X
Degraeve and Vandebroek (1998)		X			X					X		X			X				X	X			X		
Wong et al. (2000)		X			X				X			X			X				X	X			X		
de Toni and Meneghetti (2000)	X	X				X				X		X			X			X			X		X		
Wong and Chan (2001)		X			X					X		X				X			X		X				X
Wong et al. (2006)		X			X				X			X			X			X		X			X		
Ertuğrul and Tuş (2007)		X			X				X				X		X			X		X			X		
Sengupta et al. (2008)		X			X				X				X		X			X		X			X		
Karabuk (2008)	X	X				X			X			X				X			X		X				X
Amuthakkannan et al. (2010)		X			X				X			X				X			X	X			X		
Mok (2011)		X			X					X		X				X		X		X			X		
Vasant et al. (2011)		X			X				X				X			X			X	X			X		
Mok et al. (2013)		X			X				X			X				X			X		X				X
Shao et al. (2014)		X			X						X	X			X			X		X			X		
Hung et al. (2014)		X			X				X			X			X				X	X					X
Ait-Alla et al. (2014)	X	X	X				X				X	X				X		X			X				X
Zhang (2015)		X	X			X				X		X				X		X		X			X		
Rabbani et al. (2016)		X			X				X			X				X			X		X		X		
Celikbilek et al. (2016)		X			X				X			X			X				X	X			X		
Sardar et al. (2016)	X				X					X	X	X			X			X		X			X		
Felfel et al. (2016)		X	X			X				X		X				X		X			X		X		
Tesfaye et al. (2016)		X			X					X		X				X		X		X			X		
Puzovic et al. (2018)		X			X				X				X			X		X		X			X		
Wang et al. (2018)			X		X				X			X				X			X	X			X		
Campo et al. (2018)		X			X				X			X				X		X		X					X
Tsai (2018)		X			X				X			X				X		X		X			X		
Felfel et al. (2018)	X	X	X				X			X		X				X		X			X				X
Khannan et al. (2018)		X			X				X			X				X		X		X			X		
Guo et al. (2019)		X	X			X			X			X			X				X	X			X		
Lorente-Leyva et al. (2019)		X			X				X			X				X		X		X			X		
Safra et al. (2019)		X	X			X					X	X				X		X	X		X		X		
Weskamp et al. (2019)		X	X			X				X		X				X		X			X				X
Woubante et al. (2019)		X			X				X			X			X			X		X			X		
Ünal and Yüksel (2020)		X			X				X			X				X			X	X			X		
Xu et al. (2020)		X			X				X			X			X				X	X			X		
Tsao et al. (2020)		X			X				X			X			X				X	X			X		
Darvishi et al. (2020)	X	X	X				X				X	X				X		X			X				X
Yaghin et al. (2020)	X	X	X				X				X	X				X		X			X				X
Yaghin (2020)		X		X		X				X		X				X		X			X				X
Ben Abid et al. (2020)		X	X			X					X	X				X		X			X		X		
Ferro et al. (2021)		X			X					X		X			X			X		X			X		
Wang et al. (2021)		X			X						X	X				X			X		X		X		
Zhang et al. (2021)		X			X					X		X				X			X	X			X		
Ben Abid et al. (2022)		X	X			X					X	X				X		X			X		X		
Yaghin and Sarlak (2022)	X	X	X				X		X			X				X		X		X					X
Chong et al. (2022)		X	X			X					X	X			X			X		X					X
Malik et al. (2022)		X			X				X			X				X		X		X			X		
Wang et al. (2022)		X			X				X			X				X		X		X			X		
Suraiya and Hasan (2023)		X			X				X			X				X		X		X			X		
Total	10	50	14	1	34	13	5	0	29	14	10	48	4	0	20	32	0	34	19	35	17	0	37	0	15
%	19.2	96.2	26.9	1.9	65.4	25.0	9.6	0.0	55.8	26.9	19.2	92.3	7.7	0.0	38.5	61.5	0.0	65.4	36.5	67.3	32.7	0.0	71.2	0.0	28.8

Sup: Supply, Man: Manufacturing, SD: Storage and Distribution, Sal: Sales, Loc: Local, Nat: National, Int: International, ACI: Apparel and Clothing Industry, HT: Home Textile, IA: Industrial Applications, Sin: Single, Mul: Multiple, Obs: Obsolescence., ETO: Engineering-To-Order, MTO: Make-To-Order, ATO: Assembly-To-Order, MTS: Make-To-Stock.

Manufacturing one that seems to be the most relevant. It is noteworthy that only one paper considers the Sales stage, and very few considers the Supply, Storage and Distribution stages. The integration of Sales stage could require the consideration of marketing activities such as promotions, customer segmentation, marketing pricing per customer segment and, forecasting of possible demand leakage from high-priced to low-priced markets (Yaghin, 2020), among others.

As pointed out by Giri et al. (2019) one of the principal reasons behind the high waste volume is the consumer's dissatisfaction with the products. Hence, it is essential, especially for the fashion industry to become customer-centric for successfully regulating environment-friendly manufacturing practices. For achieving this, more attention should be paid to the nearest stages to the customers, that is, the Storage, Distribution and the Sales stages. This aspect is even more important when addressing international textile SCs, that remain understudied despite the existing global trade from less developed countries to more developed ones.

Instead, the SC nodes are placed mainly in the same location, being the minority that consider them situated in other locations or internationally. Therefore, to address the national and international character is a potential research field that will great impact on sustainability. This is required even more for the fashion industry and in some stages that can be usually in national or international locations such as the supply of raw materials or the distribution and sales of finished products.

The studied papers are mainly focused on the production planning of textile products, considering the entire process from the preparation, cutting of parts and manufacture of garments, as well as fashion clothing and, in some cases, the production of home textiles. The manufacture of products for industrial applications is not considered in the selected works, where the analysis of clothing processes in general is more common.

It can be seen that in last year's there is a growing tendency to address the most real situation of planning several products. Even so, there are still many works that only plan the operations of a single product that seems to be a not very realistic situation. Finally, none of the analyzed models contemplates product obsolescence, a typical feature of one of the majority sectors such as the fashion clothes. This can be justified by the fact that the SC stages considered in the research papers are centered on only one stage mainly the manufacturing one and only one paper include the Sales Stages. Therefore, it seems necessary to model this last stage and the products' obsolescence in order to better meet the needs of the final customers, minimize the products settled as well as the waste, increasing consequently the SC profits and its sustainability.

6.2. Managerial characteristics

Once identified the physical aspects of the textile SC, we proceed to analyze other functional characteristics for managing them from the operations planning viewpoint. This section presents how these management characteristics have been addressed in the works analyzed (Table 2).

6.2.1. Decision level

As it can be observed, the papers focus a little more on the tactical level (65.4 %) than on the operational one (36.5 %). Only one article that simultaneously addresses both decision levels has been found (Safra et al., 2019). At the tactical level the focus is mainly on developing medium-term models for aggregate production planning (Campo et al., 2018; Yaghin, 2020), master production planning (Lorente-Leyva et al., 2019), integration of physical supply and transportation of textile products under a social sustainability approach (Yaghin et al., 2020), integrated production–distribution planning (Ben Abid et al., 2020, 2022; Weskamp et al., 2019; Zhang, 2015) and logistics decision making (Darvishi et al., 2020).

On the other hand, at the operational level, studies are found that focus on the apparel manufacturing planning process, efficient utilization of production resources (Mok et al., 2013; Tabucanon & Estraza, 1989; Wang et al., 2021; Wong & Chan, 2001; Zhang et al., 2021), optimal machine and workshop flow scheduling (Celikbilek et al., 2016; Wong et al., 2000), sequencing of various jobs in a spinning process (Amuthakkannan et al., 2010), the scheduling of fabric cutting orders to minimize parts inventory (Degraeve & Vandebroek, 1998; Hung et al., 2014; Tsao et al., 2020; Ünal & Yüksel, 2020; Xu et al., 2020), assortment packing and collaborative shipping of fashion apparel (Wang et al., 2018).

6.2.2. Time horizon

Most of the research (67.3 %) considers a single time period and only 32.7 % contemplate multiple periods (Karacapilidis & Pappis, 1996; de Toni & Meneghetti, 2000; Wong & Chan, 2001; Karabuk, 2008; Mok et al., 2013; Ait-Alla et al., 2014; Rabbani et al., 2016; Felfel et al., 2016; Felfel et al., 2018; Safra et al., 2019; Weskamp et al., 2019; Darvishi et al., 2020; Ben Abid et a. (2020); Yaghin et al., 2020; Yaghin, 2020; Wang et al., 2021) as in the case where they perform multi-period, multi-product, multi-site supply chain production and transportation planning, and also in integrated production–distribution planning (Ben Abid et al., 2020, 2022).

6.2.3. Manufacturing strategy

From the literature analyzed, 71.2 % consider a Make-to-Order manufacturing strategy, while 28.8 % consider a Make-to-Stock strategy, these being the most common in this sector. Assemble-to-Order and Engineering-to-Order strategies have not been addressed or considered in the revised papers. Although Rabbani et al. (2016) state in their paper that they address Make-to-Order strategy, the formulation of the model has been considered in this paper as Make-to-Stock since they define inventory decision variables for final products.

6.2.4. Findings

The results show a relative balance between the tactical and operational decisional levels addressed in the papers. Only in one of them have both decision levels been considered together. It draws attention that the most used approach for the time horizon in textile operations planning is the single period horizon, typically adopted for the strategic levels (e.g., SC design). It could be partly explained for the intention to model one season. However, different time periods represent different points of time where decisions should be made, favoring the precision, flexibility and adaptability to changes. Indeed, the dynamic environment forces to develop multi-period models, even more when the improvement of flexibility and resilience is necessary to adapt solutions to ever-changing environment. Besides the consideration of some characteristics such as the setup times and costs, the demand seasonality and the obsolescence require the consideration of multiple periods.

Finally, the Make-to-Order and Make-to-Stock strategies have been the only manufacturing strategies addressed, being the first one the majority that is in concordance with Rabbani et al. (2016) that state that the Make-to-Order strategy prevails mainly in textile SCs. This trend is even more accentuated for the most recent papers. On the other hand, the Assemble and Engineering-to-Order strategies have not been addressed.

6.3. Uncertainty modelling

In addition to considering robustness as an objective, it is possible to find robust solutions by including uncertainty in the modelling approach. This section identifies the modelling context adopted for the papers revised, the uncertain type included when applicable and, in which parameters or data (Table 3).

6.3.1. Modelling context

Despite the high level of uncertainty present in the textile industry,

Table 3
Classification of Uncertainty Modelling.

References	Modelling Context		Uncertain Type				Uncertain Parameters													
	DT	UN	DB	PS	PB	SB	DM	SP	ER	MA	Costs			Available Capacity			Times			DP
											TR	PR	OP		PR	OP	TR	PR	OP	
Tabucanon and Estraza (1989)	X																			
Ford and Rager (1995)	X																			
Tomastik et al. (1995)	X																			
Karacapilidis and Pappis (1996)	X																			
Degraeve and Vandebroek (1998)	X																			
Wong et al. (2000)	X																			
de Toni and Meneghetti (2000)	X																			
Wong and Chan (2001)	X																			
Wong et al. (2006)		X		X			X											X		X
Ertuğrul and Tuş (2007)		X		X								X						X		
Sengupta et al. (2008)		X		X								X						X		
Karabuk (2008)		X			X		X				X		X							
Amuthakkannan et al. (2010)	X																			
Mok (2011)		X		X												X		X		
Vasant et al. (2011)		X		X								X						X		
Mok et al. (2013)	X																			
Shao et al. (2014)		X		X						X					X					
Hung et al. (2014)	X																			
Ait-Alla et al. (2014)		X			X	X	X				X	X								X
Zhang (2015)	X																			
Rabbani et al. (2016)	X																			
Celikbilek et al. (2016)	X																			
Sardar et al. (2016)	X																			
Felfel et al. (2016)		X			X		X													
Tesfaye et al. (2016)	X																			
Puzovic et al. (2018)	X																			
Wang et al. (2018)	X																			
Campo et al. (2018)	X																			
Tsai (2018)	X																			
Felfel et al. (2018)		X			X		X	X												
Khannan et al. (2018)	X																			
Guo et al. (2019)	X																			
Lorente-Leyva et al. (2019)	X																			
Safra et al. (2019)	X																			
Weskamp et al. (2019)		X			X		X													
Woubante et al. (2019)	X																			
(Ünal and Yüksel (2020)	X																			
Xu et al. (2020)	X																			
Tsao et al. (2020)	X																			
Darvishi et al. (2020)		X		X	X	X	X		X		X	X	X							
Yaghin et al. (2020)		X		X	X		X	X			X	X	X							
Yaghin (2020)	X																			
Ben Abid et al. (2020)		X			X		X									X				
Ferro et al. (2021)	X																			
Wang et al. (2021)		X			X	X	X								X	X				
Zhang et al. (2021)		X			X	X	X													
Ben Abid et al. (2022)	X																			
Yaghin and Sarlak (2022)		X		X			X				X	X	X		X	X				
Chong et al. (2022)	X																			
Malik et al. (2022)	X																			
Wang et al. (2022)	X																			
Suraiya and Hasan (2023)	X																			
Total	35	17	0	9	10	4	12	2	1	1	5	7	4	0	3	4	0	5	0	2
%	67.3	32.7	0.0	17.3	19.2	7.7	23.1	3.8	1.9	1.9	9.6	13.5	7.7	0.0	5.8	7.7	0.0	9.6	0.0	3.8

DT: Deterministic, UN: Uncertain, DB: Deterministic-Based, PS: Possibilistic, PB: Probabilistic, SB: Scenario-Based, DM: Demand, SP: Sales Price, ER: Exchange Rate, MA: Materials Availability, TR: Transport, PR: Processing, OP: Operating, DP: Decision-maker Penalties.

most of the models developed (67.3 %) do not include any source of uncertainty, while the rest (32.7 %) consider at least one. The works dealing with uncertainty are concentrated during 2006–2014 interval and in the last three years, although there is no concluding trend about this aspect.

6.3.2. *Uncertain type*

Among the papers analyzed, only seventeen (32.7 %) model some source of uncertainty. The uncertain type most considered has been the probabilistic (PB) or aleatory uncertainty with ten papers (19.2 %) (Ait-Alla et al., 2014; Ben Abid et al., 2020; Darvishi et al., 2020; Felfel et al., 2016, 2018; Karabuk, 2008; Wang et al., 2021; Weskamp et al., 2019;

Yaghin et al., 2020; Zhang et al., 2021), followed by the possibilistic (PS) or epistemic uncertainty in nine papers (17.3 %) (Wong et al., 2006; Ertuğrul & Tuş, 2007; Sengupta et al., 2008; Mok, 2011; Vasant et al., 2011; Shao et al., 2014; Darvishi et al., 2020; Yaghin et al., 2020; Yaghin & Sarlak, 2022). Only four papers (Ait-Alla et al., 2014; Darvishi et al., 2020; Wang et al., 2021; Zhang et al., 2021) consider the scenario-based uncertainty (7.7 %), not having found any one applying the deterministic-based uncertainty. Interestingly two recent papers consider a hybrid fuzzy-stochastic approach. Darvishi et al. (2020) proposed a hybrid fuzzy-robust stochastic programming approach to simultaneously make apparel procurement and production decisions. The fuzzy parameters include production capacity, labor and transportation variable costs, inventory holding cost and exchange rate, while the demand forecasting was considered as a stochastic parameter modelled by means a finite set of scenarios. Likewise, Yaghin et al. (2020) develop a fuzzy-stochastic approach considering the product demand stochastic meanwhile the sales prices, purchase and production costs, production times and safety stocks were modelled as fuzzy.

6.3.3. Uncertain parameters

The parameters most considered as uncertain have been demand and processing costs, with 23.1 % and 13.5 % of the models, respectively, followed by uncertainty on transportation costs (9.6 %), processing times (9.6 %), available capacity of operators (7.7 %) and machines (5.8 %), and operating costs (7.7 %). Only two papers (3.8 %) model sources of uncertainty related to cost penalties (Wong et al., 2006; Ait-Alla et al., 2014) for shortages per product unit and for delivery delays.

The rest of the uncertain parameters was considered only once in different papers representing the 1.9 % of the papers. Along these lines, only two papers (Felfel et al., 2018; Yaghin et al., 2020) address the uncertainty in apparel sale prices as the most influential parameter on total profit. Also, a unique model (Darvishi et al., 2020) consider the uncertain type exchange rate by incorporating them global purchasing decisions in fabric procurement and apparel planning. In addition, parameters such as materials availability (Shao et al., 2014) were also uncertain considered in one model. Finally, uncertainty in transportation available capacity as well as operation times of textile products and transportation are not addressed in the analyzed models.

Uncertainty parameters such as transportation, processing and operating costs were modeled both fuzzy and stochastic. The same approach is applied to parameters considering available capacity. On the other hand, processing times and materials availability were only considered as fuzzy parameters. From this, the demand is mainly modeled as a stochastic parameter and the uncertainty sources related to times, costs and sales prices, as fuzzy.

6.3.4. Findings

The analysis performed shows that there is a scarcity of models taking into account the uncertainty present in the textile industry since deterministic models are the majority. Over the last three years, the percentage of uncertain models has been increased to almost half of the total, although there is no a clear trend. When modelling the uncertainty in the textile SC operations planning, the probabilistic (aleatory) approach has been less adopted than the possibilistic (epistemic one). One reason for the lower application of the aleatory approach could be the necessity of historical data in order to derive probability distributions. Along these lines, new technologies embedded in the I4.0 context can facilitate the collection and storage of data. The recorded data would be considered as the historical data necessary to estimate their inherent probabilities. On the other hand, scenario-based approach in robust optimization has been very little considered, not being present in isolated. Despite the high number of situations with partially known information (either deterministic or totally unknown) the deterministic-based approach has not been adopted in the consulted papers providing us with an important gap.

When modelling the uncertainty much effort has been made to reflect it in aspects such as demand and costs (production, transport and operating ones). Aspects such as available transport capacity, times (operating and transport) has not been considered, and others have been little dealt with in the research carried out, such as sales prices and exchange rates, material availability, decision-maker penalties, available machinery capacity and workforce.

It is important to note that although dealing with the uncertain aspects that are present in the planning and production of the textile and apparel industry is relevant, it is very striking that very few model was developed in uncertain environment. Since this sector should face various sources of uncertainty, such as sales prices, production capacity and resources, production and delivery times (Ben Abid et al., 2020; Felfel et al., 2016; Fisher & Raman, 1996), costs and mainly customer demand (Felfel et al., 2018), it becomes essential to address the various sources of uncertainty to successfully obtain more robust and realistic results.

6.4. Model characteristics

Although the problem addressed in all the papers is the SC operations planning, depending on the SC characteristics and its scope, the decisions to be made, the objectives pursued and the constraints to be satisfied can be different as shown in Tables 4 and 5.

6.4.1. Model decisions

Indeed, as it can be appreciated in Table 4, the most used decision variable is the production quantity of textile products (75 %), which is in concordance with the fact that the majority of the models are centered on the manufacturing stage, followed by the inventory levels of materials, components and finished goods (40.4 %). Then, more operative decisions such as scheduling (19.2 %), allocation (17.3 %), lot-sizing (13.5 %) and setups (11.5 %) are considered. A few models include capacity sizing by means the overtime (23.1 %) and the number of shifts (7.7 %) definition. Decisions based on the supply quantity (7.7 %) and those related to logistics, such as transport quantity (17.3 %) or transport mode including the number of vehicles for inbound and outbound logistics (11.5 %) are also in minority. Along these lines, some authors (Wong & Chan, 2001) consider air transportation of garments, and sea-air intermodal transport of fashion products (Ben Abid et al., 2020, 2022), meanwhile others decide on multiple modes of transportation and the transport capacity sizing by means the number of required vehicles (Darvishi et al., 2020; Yaghin et al., 2020).

Decisions located downstream the SC and nearest to the customer such as Sales (13.5 %), Unmet Demand (3.8 %) and Backorder Quantity (7.7 %) are even less addressed. Only two papers regulate the impact on environmental sustainability by deciding on the energy consumption (3.8 %) and also only two works consider the waste generated (3.8 %). The most understudied decisions are those related with the capacity dimension as regards labor sizing by hiring and firing of personnel and outsourcing with only two papers dealing with it for both type of decisions (3.8 %). It is important to note that none of the models developed refer to the returns or product settlement decisions.

6.4.2. Model purpose

When deciding on the operations planning in textile SCs the economic objective is present in all of the models either by maximizing profits (Ertuğrul & Tuş, 2007; Sengupta et al., 2008; Vasant et al., 2011; Ait-Alla et al., 2014; Hung et al., 2014; Shao et al., 2014; Zhang, 2015; Rabbani et al., 2016; Tesfaye et al., 2016; Felfel et al., 2018; Tsai, 2018; Lorente-Leyva et al., 2019; Weskamp et al., 2019; Woubante et al., 2019; Yaghin, 2020; Wang et al., 2021; Yaghin & Sarlak, 2022; Chong et al., 2022; Malik et al., 2022; Suraiya & Hasan, 2023) or minimizing costs (remaining papers analyzed). It is worth mentioning the case of Felfel et al. (2018), which simultaneously maximizes the expected net profit and minimizes the measured financial risk.

Despite the importance of the environmental dimension only the

Table 4
Classification of Model Characteristics: Model Decisions.

Reference	Model Decisions																				
	SQ	TQ	TM	TCS	PQ	Set	IL	LS	Alloc	Seq	Out	LB	NS	Ove	Sal	UD	BQ	PS	Ret	EC	Was
Tabucanon and Estraza (1989)					X									X							
Ford and Rager (1995)					X																
Tomastik et al. (1995)							X	X	X												
Karacapilidis and Pappis (1996)					X	X	X			X			X								
Degraeve and Vandebroek (1998)					X	X				X											X
Wong et al. (2000)						X				X											
de Toni and Meneghetti (2000)	X				X			X		X											
Wong and Chan (2001)					X		X														
Wong et al. (2006)						X			X	X				X							
Ertuğrul and Tuş (2007)					X										X						
Sengupta et al. (2008)					X																
Karabuk (2008)	X				X		X														
Amuthakkannan et al. (2010)										X											
Mok (2011)					X																
Vasant et al. (2011)					X										X						
Mok et al. (2013)					X		X						X								
Shao et al. (2014)					X															X	
Hung et al. (2014)					X		X	X													
Ait-Alla et al. (2014)					X		X		X							X					
Zhang (2015)		X			X										X						
Rabbani et al. (2016)					X	X	X						X		X						
Celikbilek et al. (2016)										X											
Sardar et al. (2016)									X		X										
Felfel et al. (2016)		X			X		X									X					
Tesfaye et al. (2016)	X				X																
Puzovic et al. (2018)								X					X								
Wang et al. (2018)	X	X																			
Campo et al. (2018)					X		X					X									
Tsai (2018)														X						X	X
Felfel et al. (2018)		X			X		X										X				
Khannan et al. (2018)									X												
Guo et al. (2019)					X					X											
Lorente-Leyva et al. (2019)					X			X													
Safra et al. (2019)			X		X		X							X							
Weskamp et al. (2019)					X		X														
Woubante et al. (2019)									X												
(Ünal and Yüksel (2020)					X			X													
Xu et al. (2020)					X																
Tsao et al. (2020)					X	X															
Darvishi et al. (2020)		X	X	X	X		X		X					X							
Yaghin et al. (2020)		X	X	X	X		X		X					X							
Yaghin (2020)					X		X							X	X		X				
Ben Abid et al. (2020)			X		X		X							X			X				
Ferro et al. (2021)								X		X				X							
Wang et al. (2021)					X		X					X		X	X						
Zhang et al. (2021)					X																
Ben Abid et al. (2022)		X	X		X		X							X			X				
Yaghin and Sarlak (2022)		X	X		X		X							X							
Chong et al. (2022)		X			X		X								X						
Malik et al. (2022)					X																
Wang et al. (2022)									X	X											
Suraiya and Hasan (2023)					X																
Total	4	9	6	2	39	6	21	7	9	10	1	2	4	12	7	2	4	0	0	2	2
%	7.7	17.3	11.5	3.8	75.0	11.5	40.4	13.5	17.3	19.2	1.9	3.8	7.7	23.1	13.5	3.8	7.7	0.0	0.0	3.8	3.8

SQ: Supply Quantity, TQ: Transport Quantity, TM: Transport Mode, TCS: Transport Capacity Sizing, PQ: Production Quantity, Set: Setups, IL: Inventory Level, LS: Lot Sizing, Alloc: Allocation, Seq: Sequencing, Out: Outsourcing, LB: Labour Sizing, NS: Number of Shifts, Ove: Overtime, Sal: Sales, UD: Unmet Demand, BQ: Backorder Quantity, PS: Product Settlement, Ret: Returns, EC: Energy Consumption, Was: Waste.

Table 5
Classification of Model Characteristics: Model Purpose and Constraints.

Reference	Model Purpose						Model Constraints											
	Eco	Soc	Env	Flex	Rob	Res	PC	TC	SC	WC	ACC	MA	MBC	DS	SL	IC	CC	CPC
Tabucanon and Estraza (1989)	X	X					X				X			X				
Ford and Rager (1995)	X						X											
Tomastik et al. (1995)	X						X					X		X				
Karacapilidis and Pappis (1996)	X						X				X			X				
Degraeve and Vandebroek (1998)	X		X				X					X		X				
Wong et al. (2000)	X						X					X						
de Toni and Meneghetti (2000)	X			X			X				X	X						
Wong and Chan (2001)	X						X			X	X							
Wong et al. (2006)	X						X			X								
Ertuğrul and Tuş (2007)	X						X											
Sengupta et al. (2008)	X						X											
Karabuk (2008)	X						X		X					X				
Amuthakkannan et al. (2010)	X						X											
Mok (2011)	X						X			X								
Vasant et al. (2011)	X						X											
Mok et al. (2013)	X						X				X							
Shao et al. (2014)	X		X				X						X					
Hung et al. (2014)	X		X								X		X	X				
Ait-Alla et al. (2014)	X				X		X		X					X				
Zhang (2015)	X						X				X							
Rabbani et al. (2016)	X		X							X			X	X				
Celikbilek et al. (2016)	X													X				
Sardar et al. (2016)	X		X	X							X			X		X	X	
Felfel et al. (2016)	X	X			X		X	X	X				X					
Tesfaye et al. (2016)	X						X					X						
Puzovic et al. (2018)	X											X						
Wang et al. (2018)	X							X						X				
Campo et al. (2018)	X						X		X				X	X				
Tsai (2018)	X		X				X											
Felfel et al. (2018)	X				X		X	X					X	X				
Khannan et al. (2018)	X						X		X									
Guo et al. (2019)	X							X										
Lorente-Leyva et al. (2019)	X	X									X		X	X				
Safra et al. (2019)	X						X	X	X									
Weskamp et al. (2019)	X						X	X	X				X					
Woubante et al. (2019)	X						X					X						
(Ünal and Yüksel (2020)	X											X						
Xu et al. (2020)	X													X				
Tsao et al. (2020)	X													X				
Darvishi et al. (2020)	X				X		X	X	X	X	X		X	X				
Yaghin et al. (2020)	X	X			X		X	X		X	X		X	X				
Yaghin (2020)	X						X		X	X			X	X				
Ben Abid et al. (2020)	X	X					X	X	X					X				
Ferro et al. (2021)	X						X							X				
Wang et al. (2021)	X	X	X									X		X	X			
Zhang et al. (2021)	X		X				X											
Ben Abid et al. (2022)	X	X					X		X		X		X	X				
Yaghin and Sarlak (2022)	X	X	X				X			X	X		X					
Chong et al. (2022)	X								X					X	X			
Malik et al. (2022)	X										X							
Wang et al. (2022)	X						X				X							
Suraiya and Hasan (2023)	X						X					X						
Total	52	8	9	2	5	0	38	9	12	8	15	10	13	24	2	1	1	0
%	100	15.4	17.3	3.8	9.6	0.0	73.1	17.3	23.1	15.4	28.8	19.2	25.0	46.2	3.8	1.9	1.9	0.0

Eco: Economic, Soc: Social, Env: Environmental, Flex: Flexibility, Rob: Robustness, Res: Resilience, PC: Productive Capacity, TC: Transport Capacity, SC: Storage Capacity, WC: Workforce Capacity, ACC: Aggregate Capacity Constraints, MA: Materials Availability, MBC: Material Balance Constraints, DS: Demand satisfaction, SL: Service level, IC: International Constraints, CC: Contracts Constraints, CPC: Company Policy Constraints.

17.3 % of the models include it in their objectives by minimizing carbon emissions, energy consumption, water use and wastes (Degraeve & Vandebroek, 1998; Hung et al., 2014; Rabbani et al., 2016; Sardar et al., 2016; Shao et al., 2014; Tsai, 2018; Wang et al., 2021; Yaghin & Sarlak, 2022; Zhang et al., 2021).

The social dimension is addressed to an even lesser extent in only 15.4 % of the studies, primarily in terms of minimize lateness by meeting delivery dates (Tabucanon & Estraza, 1989), lost customer demand level (Felfel et al., 2016), and maximizing service level and customer satisfaction (Ben Abid et al., 2020, 2022; Lorente-Leyva et al., 2019). The social dimension of sustainability is also considered in a criteria related to working conditions and social investment in the supply chain (Yaghin & Sarlak, 2022; Yaghin et al., 2020), and employment changing (Wang et al., 2021).

Only 3.8 % of the models consider the flexibility dimension by maximizing the ability to manage and easily adjust to the unforeseen events presented, with the objective of achieving higher levels of productivity; providing the planning system with a high degree of responsiveness, when considering the low predictability and turbulence of the market (de Toni & Meneghetti, 2000); also in maximizing the flexibility and capacity of the textile supply chain considering the uncertainties and global dynamics of the production environment (Sardar et al., 2016), allowing companies to adapt in a cost-effective manner.

The robustness dimension was considered in 9.6 % of the models, in the capacity maximization to cope with disturbances and maintain the productive system performance at a high level; considering the risks and uncertainty present to maintain stability in the face of changes in the textile environment (Ait-Alla et al., 2014; Felfel et al., 2016, 2018); also in obtaining robust models and solutions to face the uncertainty of demand and supply of global textile products (Darvishi et al., 2020; Yaghin et al., 2020). Finally, resilience is not addressed as an objective in any work studied.

6.4.3. *Model constraints*

The most considered constraints were those related to the productive capacity (73.1 %), followed by the constraints related to demand satisfaction (46.2 %) and aggregate capacity constraints (28.8 %). Some papers considered materials balance constraints (25 %), for example, related to inventory (Darvishi et al., 2020; Felfel et al., 2018; Rabbani et al., 2016; Shao et al., 2014) or materials availability (19.2 %) also determining, the existence of final and intermediate products.

Facility storage capacity was considered as a constraint in 23.1 % of the models (Ait-Alla et al., 2014; Ben Abid et al., 2020, 2022; Campo et al., 2018; Chong et al., 2022; Darvishi et al., 2020; Felfel et al., 2016; Karabuk, 2008; Khannan et al., 2018; Safra et al., 2019; Weskamp et al., 2019; Yaghin, 2020), and transportation capacity (17.3 %) (Ben Abid et al., 2020; Darvishi et al., 2020; Felfel et al., 2016, 2018; Guo et al., 2019; Safra et al., 2019; Wang et al., 2018; Weskamp et al., 2019; Yaghin et al., 2020). Other constraints included workforce capacity (Darvishi et al., 2020; Mok, 2011; Rabbani et al., 2016; Wong & Chan, 2001; Wong et al., 2006; Yaghin & Sarlak, 2022; Yaghin et al., 2020; Yaghin, 2020), minimum service level (Chong et al., 2022; Wang et al., 2021), contractual constraints (Sardar et al., 2016) as well as international constraints (Yaghin, 2020) referring to policies. None of the models integrate constraints referring to firms' own policies.

6.4.4. *Findings*

In a dynamic environment, rapidly adaptation to changes require to give more attention to the capacity sizing. Therefore, given the characteristics of the textile industry, it would be interesting to develop models that consider to a greater extent, the labor sizing, number of shifts and overtime. To match supply and demand diminishing waste, more attention should be paid to decisions affecting the supply, distribution and fulfillment of customer's requirements. Along these lines the inclusion of backorders, unsatisfied demand and settle products will be of relevance for final textile products.

It draws attention that despite the predominant role that the sustainability practices are acquiring in the textile industry (Desore & Narula, 2018; Kazancoglu et al., 2020; Lenzo et al., 2018; Luo et al., 2021; Maia et al., 2019; Mohsin & Sardar, 2019; Peters & Simaens, 2020; Roy et al., 2020; Youn & Jung, 2021; Lombardi Netto et al., 2021), the developed models consider very little decisions crucial for the environmental point of view such as the transported quantities and transportation modes, CO_2 emissions, energy and water consumption, waste and returns. Indeed, the topic of reverse logistics from the optimization and intelligent point of view at the tactical level seems to be unexplored.

This is in line with the finding that most of the models do not contemplate any objective related to environmental impact and only two recent works (Wang et al., 2021; Yaghin & Sarlak, 2022) integrate the three dimensions of sustainability simultaneously. Again, this is an indication that the optimization and intelligent tools developed for the operations planning in the textile industry are not aligned with the concern for sustainable practices in other research areas in this sector. Indeed, the residues, waste and wastewater generated by textile processes, mainly dyeing of fabrics, manufacture of synthetic fibers and spinning, directly affect the environment. Therefore, there is a need to develop models for planning operations in a sustainable manner that consider environmental dimensions, through the minimization of waste, water and energy use, and environmental pollution. Besides, social aspects should be included in the models not only in terms of customer satisfaction but also in terms of worker conditions, especially for the global textile SCs. Even more relevant is to find solutions that optimize the three dimensions of sustainability simultaneously which is an unexplored field.

Even less attention has been paid to other objectives, especially those related with flexibility and robustness. The textile industry needs to provide robust solutions that adapt adequately to the uncertainty present. A surprising finding is related to the non-existence of models that consider resilience in the operations planning of textile SCs, constituting an important gap to be covered, given the lessons learned with the pandemic situation of COVID-19.

As regards the constraints considered in the decision support tools developed, there is a lack of constraints reflecting the direct material flow along the entire textile SC and its associated balancing equations from raw material suppliers to final consumers and flow in the opposite direction for cases such as the reverse logistics. This fact comes to corroborate the scarcity of works dealing with the whole textile SC. Although the productive capacity has been addressed at the manufacturing stage, it should be mentioned that transportation, warehouse and labor force limitations have been included in a very marginal way. Formulation of constraints linking the customer demand with the finished good supply and to ensure a certain service level are also minority. Very little attention has been paid to functional aspects and policies not only from the own company but also related with local, national or international policies, rules or contracting constraints. Therefore, it can be stated that there is a vast room for research.

6.5. *Resolution approach*

Once characterized the different problems addressed in the papers, it is time to analyze how they are modeled, their solution context and their validation. This analysis will also identify the main characteristics and learning ability of the developed solutions (Tables 6 and 7). As it can be observed the percentages sum of Mathematical Programming Models, Heuristics and AI applications exceed 100 %, since there are papers that combine these methods in the resolution of the problems presented being them identified also as hybrid methods.

6.5.1. *Modelling technique*

The majority of the papers (75 %) pursued a single objective related mainly with the economic dimension of sustainability (profit maximization or cost minimization). Only thirteen models (25 %), aimed at optimizing multiple objectives simultaneously. For example, Tabucanon and Estraza (1989) considered the maximization of revenue and minimization of lateness, minimization of production cost and minimization of overtime. Mok (2011) maximizes the on-time completion rate and minimize the variance due to different sorts of uncertainties. Shao et al. (2014) optimize the production plan by minimizing deviation variables of the expected value and minimizing energy consumption. Sardar et al. (2016) minimize operational costs, penalty costs for each domestic supplier as a function of reserved capacity flexibility and minimize outsourcing risks in an international subsidiary with international suppliers. Wang et al. (2018) minimize total costs, including the value of overload and underload fashion clothing items, truck and shipping cost. Ben Abid et al. (2020) minimize total costs and maximize the customer satisfaction level in terms of on-time delivery. Felfel et al. (2018) maximize the expected net profit and minimize the financial risk. In

Table 6
Classification of the Resolution Approach: Number of Objectives and Modelling Technique.

Reference	N° Obj		Mathematical Programming Model									HM	Artificial Intelligence Methods						
	Sin	Mul	LP	ILP	MILP	NLP	MO	SP	RO	IM	GR		MM	FL&FS	NN	ES	ML	MAS	HYM
Tabucanon and Estraza (1989)		X	X				X												
Ford and Rager (1995)	X															X			
Tomastik et al. (1995)	X			X								X							X
Karacapilidis and Pappis (1996)	X											X							
Degraeve and Vandebroek (1998)	X				X														
Wong et al. (2000)	X												X						
de Toni and Meneghetti (2000)	X				X							X							X
Wong and Chan (2001)	X												X						
Wong et al. (2006)	X												X	X					X
Ertuğrul and Tuş (2007)	X		X											X					X
Sengupta et al. (2008)	X		X											X					X
Karabuk (2008)	X				X			X				X							
Amuthakkannan et al. (2010)	X												X						
Mok (2011)		X					X						X	X					X
Vasant et al. (2011)	X		X											X					X
Mok et al. (2013)	X												X						
Shao et al. (2014)		X					X						X	X	X		X	X	X
Hung et al. (2014)	X				X							X							X
Ait-Alla et al. (2014)	X							X	X										
Zhang (2015)	X				X														
Rabbani et al. (2016)	X				X														
Celikbilek et al. (2016)	X				X								X						X
Sardar et al. (2016)		X					X												
Felfel et al. (2016)		X					X	X											
Tesfaye et al. (2016)	X		X																
Puzovic et al. (2018)	X											X							
Wang et al. (2018)		X				X	X												
Campo et al. (2018)	X		X																
Tsai (2018)	X				X														
Felfel et al. (2018)		X					X	X											
Khannan et al. (2018)	X		X																
Guo et al. (2019)	X											X	X						X
Lorente-Leyva et al. (2019)	X				X								X						X
Safra et al. (2019)	X			X															
Weskamp et al. (2019)	X							X											
Woubante et al. (2019)	X		X																
(Ünal and Yüksel (2020)	X					X													
Xu et al. (2020)	X			X									X						X
Tsao et al. (2020)	X				X								X						X
Darvishi et al. (2020)	X					X		X	X					X					X
Yaghin et al. (2020)	X					X		X						X					X
Yaghin (2020)	X					X													
Ben Abid et al. (2020)		X			X		X	X											
Ferro et al. (2021)	X												X						
Wang et al. (2021)		X			X		X	X											
Zhang et al. (2021)		X					X	X											
Ben Abid et al. (2022)		X		X			X												
Yaghin and Sarlak (2022)		X				X	X							X					X
Chong et al. (2022)	X																X		
Malik et al. (2022)		X					X												
Wang et al. (2022)	X			X															
Suraiya and Hasan (2023)	X		X																
Total	39	13	9	5	12	6	13	10	2	0	0	7	13	9	1	1	2	1	17
%	75.0	25.0	17.3	9.6	23.1	11.5	##	19.2	3.8	0.0	0.0	13.5	25.0	17.3	1.9	1.9	3.8	1.9	32.7

Sin: Single, Mul: Multiple, LP: Linear Programming, ILP: Integer Linear Programming, MILP: Mixed Integer Linear Programming, NLP: Non-linear programming and mixed integer/integer nonlinear programming, MO: Multi-objective Programming, SP: Stochastic Programming, RO: Robust Optimization, IM: Interval Modelling; GR: Grey Programming, HM: Heuristic Methods, MM: Metaheuristic Methods, FL&FS: Fuzzy Logic and Fuzzy Sets, NN: Neural Networks, ES: Expert Systems, ML: Machine Learning, MAS: Multi-Agent Systems, HYM: Hybrid Models.

textile manufacturing, Zhang et al. (2021) minimize the total tardiness of production orders and excessive carbon emissions, and Yaghin and Sarlak (2022) optimize total profit, late deliveries of raw materials, social value of purchases and carbon emissions of supply chain.

As regards the modelling techniques, the mathematical programming is the most used with 78.8 % of the studies, followed by the AI with 46.2 % being the heuristics the least common with 13.5 %. From them, the percentage of the papers that have applied in isolated these techniques are 48.1 % for mathematical programming, 15.3 % for AI techniques and 3.8 % for heuristic methods, meanwhile the

Table 7
Classification of the Model Approach: Solution Environment and Model Validation.

Reference	Solution Environment				Model Validation	
	Static	Dynamic		Smart	Case Study	Real Case
		Re-planning by period	Re-planning by event			
Tabucanon and Estraza (1989)	X					X
Ford and Rager (1995)	X				X	
Tomastik et al. (1995)	X					X
Karacapilidis and Pappis (1996)	X				X	
Degraeve and Vandebroek (1998)	X					X
Wong et al. (2000)	X					X
de Toni and Meneghetti (2000)		X				X
Wong and Chan (2001)		X			X	
Wong et al. (2006)	X					X
Ertuğrul and Tuş (2007)	X					X
Sengupta et al. (2008)	X				X	
Karabuk (2008)		X			X	
Amuthakkannan et al. (2010)	X				X	
Mok (2011)	X				X	
Vasant et al. (2011)	X				X	
Mok et al. (2013)			X	X		X
Shao et al. (2014)	X			X		X
Hung et al. (2014)	X				X	
Ait-Alla et al. (2014)		X		X	X	
Zhang (2015)	X				X	
Rabbani et al. (2016)	X					X
Celikbilek et al. (2016)	X				X	
Sardar et al. (2016)	X				X	
Felfel et al. (2016)		X				X
Tesfaye et al. (2016)	X				X	
Puzovic et al. (2018)	X				X	
Wang et al. (2018)	X				X	
Campo et al. (2018)	X				X	
Tsai (2018)	X				X	
Felfel et al. (2018)		X				X
Khannan et al. (2018)	X				X	
Guo et al. (2019)	X				X	
Lorente-Leyva et al. (2019)	X					X
Safra et al. (2019)		X			X	
Weskamp et al. (2019)		X			X	
Woubante et al. (2019)	X				X	
(Ünal and Yüksel (2020)	X				X	
Xu et al. (2020)	X				X	
Tsao et al. (2020)	X				X	
Darvishi et al. (2020)		X		X	X	
Yaghin et al. (2020)		X		X	X	
Yaghin (2020)		X			X	
Ben Abid et al. (2020)		X		X		X
Ferro et al. (2021)	X				X	
Wang et al. (2021)		X		X	X	
Zhang et al. (2021)	X			X		X
Ben Abid et al. (2022)		X				X
Yaghin and Sarlak (2022)		X			X	
Chong et al. (2022)		X				X
Malik et al. (2022)	X				X	
Wang et al. (2022)	X				X	
Suraiya and Hasan (2023)	X					X
Total	35	16	1	8	34	18
%	67.3	30.8	1.9	15.4	65.4	34.6

remaining percentage have been jointly combined with other techniques giving rise to 17 hybrid approaches (32.7 %).

Related to mathematical programming models, the type most employed are LP and MILP, with 17.3 % and 23.1 % of the analyzed models, respectively, followed by NLP models (11.5 %). Only five models employed ILP (Ben Abid, Ayadi, & Masmoudi, 2022; Safra et al., 2019; Tomastik et al., 1995; Wang et al., 2022; Xu et al., 2020). For green production planning and control in textile industry, it is worth mentioning the work of Tsai (2018) who developed a mathematical programming model combined with Industry 4.0 technologies. They used various sensors to collect and monitor data from production operations and performed real-time sensing system to control production, achieving carbon emission reduction, energy saving and waste reuse. They also developed a MILP model to find the best mix of textile products to maximize the profit. Multi-objective programming (MO) methods were implemented in 25 % of the papers. With the exception of Wang et al. (2018), all of them adopt an aggregated method. The goal programming (GP) approach is used by (Malik et al., 2022; Sardar et al., 2016; Shao et al., 2014; Tabucanon & Estraza, 1989; Wang et al., 2021) while the epsilon-constrained method is applied in (Ben Abid et al., 2020, 2022; Felfel et al., 2016, 2018; Yaghin & Sarlak, 2022). On its part, Mok (2011) applies a multi-objective genetic algorithm (MOGA), and Zhang et al. (2021) propose a multi-objective evolutionary stochastic optimization approach based on parallel evolution and scenario generation.

The SP approach was less applied, only in the 19.2 % of the models (Ait-Alla et al., 2014; Ben Abid et al., 2020; Darvishi et al., 2020; Felfel et al., 2016, 2018; Karabuk, 2008; Wang et al., 2021; Weskamp et al., 2019; Yaghin et al., 2020; Zhang et al., 2021). Robust optimization was applied in only 3.8 % (Ait-Alla et al., 2014; Darvishi et al., 2020) not having found any work implementing neither the interval method nor the grey programming.

A more minority approach adopted corresponds to the heuristic methods (13.5 %) that tries to find a satisfactory solution in a reasonable time. Tomastik et al. (1995) develop a heuristic method using Lagrangian relaxation technique to solve the problem of scheduling and resource allocation in high volume apparel production. Karacapilidis and Pappis (1996) propose an interactive model-based system for the management of production in textile production systems focusing on the Master Production Scheduling. Similarly, other authors develop heuristic methods to obtain faster and more flexible results by elaborating production plans (de Toni & Meneghetti, 2000), minimizing the inventory of cut parts (Hung et al., 2014), determining lot sizes with lower cost (Puzovic et al., 2018) and solving the vehicle assignment, parallel machine and distribution scheduling problem by combining intelligent optimization techniques with heuristic procedures (Guo et al., 2019). With the application of these methods to the problems under study, very good results were obtained considering both the quality and the computational times of the solutions found.

Slightly less than half of the articles (46.2 %) applied AI methods which represents an important percentage. The metaheuristic methods are the most widely employed (25 %) mainly used to reduce the computational effort such as heuristic methods. Fuzzy Logic and Fuzzy Sets, with 17.3 % of the research, were applied for modelling parameter uncertainty or vagueness. Some papers (Wong et al., 2006; Mok et al., 2013; Shao et al., 2014) combine Fuzzy Theory with Metaheuristic Methods for the modeling and solution of the problems encountered. The rest of AI techniques able to provide some smart and intelligent character to the operations planning were hardly addressed in the literature. It should be noted that in the textile SC operations planning, little attention has been paid to the application of AI methods such as Neural Networks (NN), Machine Learning (ML) and Multi-Agent Systems (MAS). All these methods were addressed in Shao et al. (2014) that developed hybrid intelligent algorithm based on fuzzy approach, neural network, and genetic algorithm to solve the optimum problem of production planning. The work developed by Chong et al. (2022) optimizes an apparel supply chain using deep reinforcement learning. Finally, only Ford and Rager (1995) (1.9 %), applied the Expert Systems (ES) approach to support the production planning of a final textile product, considering the whole manufacturing process and the resource allocation, with the aim of increasing quality and reducing costs.

It is important to highlight that a large part of the models (32.7 %) was hybrid, which means that more than one of the modeling approaches and techniques mentioned above were combined. The most common combination of methods is Metaheuristics with Fuzzy Logic and Fuzzy Sets (Mok, 2011; Shao et al., 2014; Wong et al., 2006). These works use fuzzy set theory to model the uncertain parameters present in the analyzed environments and combine them with AI methods, mainly metaheuristic to improve the resolution time of the production planning and operations problem in the textile industry. Other hybrid models that have been among the most used, were that combining Linear Programming (Ertuğrul & Tuş, 2007; Sengupta et al., 2008; Vasant et al., 2011) and more recently Non-Linear Programming (Darvishi et al., 2020; Yaghin & Sarlak, 2022; Yaghin et al., 2020) with Fuzzy Logic and Fuzzy Sets, suitable when the textile SC uncertainty is characterized by vagueness. Finally, only four models (de Toni & Meneghetti, 2000; Hung et al., 2014; Karabuk, 2008; Tomastik et al., 1995), combine mathematical programming techniques with heuristics.

6.5.2. Solution environment

Although the dynamism present in the textile SCs, the majority of the models are solved in a static context (67.3 %). Just the 32.7 % of the papers (Ait-Alla et al., 2014; Ben Abid, Ayadi, & Masmoudi, 2022; Chong et al., 2022; Darvishi et al., 2020; de Toni & Meneghetti, 2000; Felfel et al., 2016, 2018; Karabuk, 2008; Mok et al., 2013; Safra et al., 2019; Wang et al., 2021; Weskamp et al., 2019; Wong & Chan, 2001; Yaghin & Sarlak, 2022; Yaghin et al., 2020; Yaghin, 2020) contemplates the solution in a dynamic environment mainly by means the re-planning per period (30.8 %) and punctually only one through executing the re-planning by event (Mok et al., 2013) in order to adapt the planning solution to the environment each time an unforeseen event occurred. It should be noted that only eight models (15.4 %) considered an intelligent solution environment, mainly in training in various scenarios (Ait-Alla et al., 2014; Ben Abid et al., 2020; Darvishi et al., 2020; Wang et al., 2021; Yaghin et al., 2020; Zhang et al., 2021) and in real environments (Mok et al., 2013; Shao et al., 2014).

6.5.3. Model validation

The validation of the proposals is applied to case studies (65.4 %), while the remaining (34.6 %) to real applications. Paradoxically, despite of the massive availability of data provided by the new technologies, it can be observed that the validation of models through case studies with simulated but not real data are increasing in recent years. Therefore, the research in this field focuses on case studies, paying less attention to real cases.

6.5.4. Findings

The result of this dimension reveals that problems including uncertainty have been mainly modelled by fuzzy sets and/or stochastic programming. Some uncertainty modelling techniques have been underexplored (robust optimization (RO)), meanwhile others have not been applied in the papers revised, such as interval modelling (IM) and grey programming (GR). This represents an important gap detected in the literature.

In order to find sustainable solutions aligned with the trend of textile practices in the reality, it is necessary to develop models that consider multiple objectives simultaneously. Despite this fact, only the 25 % of the models consider more than one objective with a slight upward trend in the latest works. Despite this, only one employ non-aggregated MO techniques, that shows the little contribution of existing models to sustainability, arising the necessity of future research in the MO field with more sophisticated techniques to achieve sustainable textile SCs.

The development of heuristic methods has been little in recent years. In contrast, there has been a remarkable increase in the application of AI methods, mainly of the metaheuristic methods in presence of combinatorial problems in order to achieve satisfactory results faster. This is a very promising approach to increase the flexibility and resilience in the textile operations planning. It also awakens the interest of researchers in solving problems related to textile production, even more so under complex and uncertain conditions by means fuzzy logic and fuzzy sets. It is important to point out that very little attention was paid to other methods related to neural networks, machine learning, multi-agent systems and expert systems, being practically insignificant their use in the analyzed literature. Therefore, there is an important gap in the literature to explore the learning capabilities of this methods. Besides, there are also very few comparative studies that evaluate the advantages and disadvantages of the different methods applied in the solution of complex problems related to the textile operations planning.

The current environment requires textile SCs to be flexible, robust and resilient. Therefore, it is necessary to develop models that adapt to the dynamic and uncertain environment in which the textile industry operates. For that, dynamic re-planning will be necessary not only by period but also by event. This increase in the solution frequency will be accompanied with shorter solution times to increase SC resilience, therefore the learning capability of certain AI methods such as machine learning or expert systems, will be very useful for that. Despite this, the literature review reveals that most of the models are solved only once assuming a static situation. Therefore, there is a need for taking advantage of the availability of data in real time in order to adapt to the changing environment through re-planning by event. Besides, the experience acquired in the model executions in practical environments or in different scenarios should be considered, and the lessons learned should be incorporated for improving learning capabilities that, in turn, will allow a more rapid and better reaction to unforeseen events. Finally, it is necessary to develop models taking into account the complexity of real textile SCs and validate them by means real cases.

7. Conclusions and future research lines

Under real conditions, operations planning in the textile industry becomes a very dynamic and complex process involving multiple interrelated decisions to respond to demand fluctuations under multiple sources of uncertainty. Therefore, it is necessary to develop decision support tools that allow the sustainable, smart and dynamic operations planning of textile SCs. To achieve this, optimization models such as mathematical programming ones, heuristic methods and AI techniques were identified as suitable ones. Being aware of the gap existing in the literature, a CF has been proposed to characterize the textile SCOP, analyze existing research and support the development of AI and mathematical programming models to achieve sustainable and smart textile SCs in a dynamic and uncertain context. The managerial and research implications derived from the results obtained in this research are described below as well as future research lines.

7.1. Managerial and research implications

The utility of the CF and the structured literature review for managers and researchers is manifold. As its own definition indicates (Miles & Huberman, 1994), a CF serves to characterize the key elements or building blocks necessary to identify and document the domain under study, the textile SCOP for this case, as well as their relationships. Along these lines, the CF jointly with the literature revision offers several advantages from the **managerial viewpoint**:

1. Firstly, the CF constitutes a tool for the understanding among non-academics (such as managers), and academics (such as researchers) in order to understand themselves and precisely define the problem under study, that is, to characterize the problem to be addressed.
2. Secondly, the CF can be used as a reference model that integrates the necessary parts/elements and their possible values for the subsequent development of particular models to support the textile SCOP problem characterized in the first point. Therefore, the CF can be used as a template to provide us with the more relevant aspects when modelling one specific textile SCOP, by means its dimensions and categories, and also to guide the decisions on what aspects to model and how, by means its elements. Indeed, reference models can be considered as generic conceptual models that formalize recommended practices for a given domain (Pesic & van der Aalst, 2005), being the domain for this case, the textile SCOP. Similarly, the result of modelling on different particular domains (the specific papers revised for textile SCOP) allows the extraction of similar characteristics which enables the construction of the reference model. This definition is consistent with steps 3 and 4 of the research methodology in which the updating of the tentative versions of the CF are derived from the literature review performed (particular domains).
3. The CF, jointly with the structured literature review, present the advantage of accelerating the development of particular AI and Mathematical Programming Models since it provides a repository of them (Fettke & Loos, 2003) analysed in a structured way being easily comparable. The use of the CF to characterize the problem under study, as pointed out in the first point, facilitates the identification of existing models dealing with same common characteristics of the textile SCOP problem under study. Therefore, these previous works can be taken as a basis to model and solve the problem under study.

Besides to all the previous managerial advantages, some additional positive implications exist from the research and academic viewpoint:

4. The structured literature revision based on the CF, allows researchers to identify current gaps, focus their efforts and direct their future work.
5. Besides, researchers can also use the CF to review forthcoming research in a structured way. This can support researchers to devise the future research trends.

The application of the CF to develop AI and mathematical programming models for the textile sector promotes the development of sustainable and smart operations planning of the textile SCs in a dynamic and uncertain context. This is due to the special focus of the CF on these aspects by means the definition of different dimensions and categories related to them. More specifically, the sustainability aspect is addressed in the category “model purpose” of the dimension “model characteristics” in which the three dimensions of sustainability are described jointly with works addressing them in different ways. To model the triple bottom line of sustainability requires the development of multi-objective programming models whose general description is made in the dimension of “Resolution approach”.

The uncertain and dynamic environment of textile sector, stressed by its increasingly international scope, forces to take into account additional objectives related with flexibility, robustness and resilience. These objectives are studied also in the category of “Model Purpose” belonging to the dimension of “Model characteristics”. Besides, the CF makes special emphasis on uncertainty by defining the dedicated category of “Uncertainty Characterization” and different techniques of addressing it in the “Resolution approach”.

On its part, the dynamic and smart character when planning the operations of textile SCs, is analysed in “Solution Environment” of the dimension “Resolution Approach”. The description of this CF category jointly with the literature analysis provides insights about the necessity of define dynamic and smart solutions. This is a requirement in the ever-changing and uncertain environment for which the technologies associated with I4.0 offer the availability of real-time data, processing and learning capabilities associated with AI.

7.2. Future research lines

From the structured literature revision based on the CF, it can be concluded that more realistic models should be developed that consider multiple products, the whole stages of textile SCs leading to sustainable business orientation not only for B2C but also for B2B2C and the international character. It is required that further optimization and intelligent techniques consider the small-scale as well as largescale operations of this sector. Due to rapid changes in worldwide customer demand, the obsolescence character should be managed, especially for some textile products such as the fashion clothes. This also leads to include the most downstream stage of the SC, the Sales Stage in B2C scenario, as well as some decision variables (e.g., backorders, product settlement) in order to properly match supply and demand reducing also wastes and returns.

Besides, to move towards more flexible textile SCs, it is necessary to define multi-period models where decisions should be made at each time period. This should be accompanied with the definition of decision variables that provide the properly capacity dimension as required. Therefore, greater attention should be paid to the inclusion of capacity dimension in the decision support models in order to better adapt to the dynamic environment (for instance, labor sizing, number of shifts and overtime).

It draws attention that despite the great and growing concern of sustainability in textile industries, this aspect is not conveniently included in the models neither through decision variables (e.g., CO_2 emissions, energy and water consumption, waste and returns) nor through their corresponding objectives as regards its environmental and social dimensions. In fact, there is no model optimizing all three sustainability dimensions simultaneously. Existing research basically pursued economic objectives and only very few considered environmental or social ones being, even less, those including the flexibility and robustness in their objectives. Those are devised as an unexplored field jointly with the nowadays relevant objective of maximizing the SC resilience.

In order to improve the robustness of the operations plans finally implemented, the inclusion of uncertainty in the modelling approach is of crucial relevance. Despite the large number of uncertain sources in the textile sector a little more than the 25 % of the models consider it. The most used approach is the fuzzy one, being the stochastic one less implemented due to the necessity of more accurate availability of historical data. Although this limitation can be overcome by means the I4.0 technology that capture and store data on real time, the solution complexity remains still a barrier to implement it. Very few models integrate the fuzzy and stochastic approaches adopting a hybrid one. This hybrid modelling approach represent, indeed, the most real situation where some parameters can be model as stochastic while other as fuzzy. Understudied uncertainties are those related to decision-maker penalties for shortages or delivery delays as well as currency changing rates.

The application of solution methods in scenarios with deterministic input information and single objectives to be solved, represent the most addressed situation by means LP, MILP and metaheuristic methods. However, in multiple scenarios, when considering all the parameters involved, their uncertainty as well as multiple objectives, to employ one isolated modelling technique can become unfeasible and inefficient in terms of accuracy and computational time, among others. In general, it was detected that, almost in the half of the analyzed research, different methods have been hybridized to solve the problems present in textile production, even more in conditions of uncertainty and a multiple period time horizon. However, the application of AI techniques has centered on overcoming the complexity limitation of the models and the uncertain modelling. There is an important gap to implement models that consider the learning capabilities of AI in order to improve the resilience and flexibility of the textile SCs. This should be accompanied with the design of models to be executed in a dynamic way not only re-planning by period but also by event in an intelligent fashion. For that, the availability of real-time data in the I4.0 context should be of relevance.

In short, there is a very wide field to develop optimization support tools that consider the complex characteristics of real textile SCs incorporating the three dimensions of sustainability in a dynamic fashion provided by the re-planning capabilities and the inclusion of uncertainty. This jointly with the use of the learning features of AI methods will allow more resilient and smarter textile SCs.

CRediT authorship contribution statement

Leandro L. Lorente-Leyva: Conceptualization; Methodology; Validation; Formal analysis; Investigation; Data curation; Software; Writing - Original draft; Visualization. **M.M.E. Alemany:** Conceptualization; Methodology; Formal analysis; Investigation; Supervision; Validation; Writing - Original draft; Writing - Review & editing. **Diego H. Peluffo-Ordóñez:** Formal analysis; Methodology; Supervision; Validation; Writing - Original draft; Writing - Review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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