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Optimization of human-aware logistics and manufacturing systems: A comprehensive review of modeling approaches and applications

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ABSTRACT

Historically, Operations Research (OR) discipline has mainly been focusing on economic concerns. Since the early 2000s, human considerations are gaining increasing attention, pushed by the growing societal concerns of sustainable development on the same terms as the economic and ecological ones. This paper is the first part of a work that aims at reviewing the efforts dedicated by the OR community to the integration of human factors into logistics and manufacturing systems. A focus is put on the modeling and solution approaches used to consider human characteristics, their practical relevance, and the complexity induced by their integration within optimization models. The material presented in this work has been retrieved through a semi-systematic search of the literature. Then, a comprehensive analysis of the retrieved corpus is carried out to map the related literature by class of problems encountered in logistics and manufacturing. These include warehousing, vehicle routing, scheduling, production planning, and workforce scheduling and management. We investigate the mathematical programming techniques used to integrate human factors into optimization models. Finally, a number of gaps in the literature are identified, and new suggestions on how to suitably integrate human factors in OR problems encountered in logistics and manufacturing systems are discussed.

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Preamble

Given the large volume of material reviewed, which does not enable the authors to present a substantive analysis in a single paper, the current literature review has been split into two separate papers (parts), that are highly connected. We refer to the present paper as the *first part*, and to its twin paper (Prunet et al., 2024) as the *second part*. Although an introduction is present in both parts, the scope definition, the positioning within the landscape of the related literature, and the methodology applied to collect the relevant material are only discussed in detail in the first part. Then, the retrieved corpus is studied and discussed by adopting three different points of view:

- *Application area*, where we discuss how human factors are treated in each class of problem within the logistics and manufacturing communities. This work is presented in the first part, Sections 4–6. The results of the material collection are provided with tables in these sections.
- *Human factors*, where we discuss which human factors are investigated. For each factor, we study the *Human-Aware Models* used to model and quantify it, and the advantages and limitations of such models. This is done in the second part, Sections 3–8.
- *Mathematical optimization*, where we discuss the integration of human-aware considerations within optimization models. The study focuses on the impact on the models, in terms of objective function, constraints, parameters, and the associated complexity burden. This is done in the first part, Section 7.

As an illustration, let us consider a paper studying an assembly line balancing problem that accounts for the ergonomic risk related to awkward posture by imposing a maximal exposure at each workstation. The paper is discussed in terms of *application* as an assembly line in Section 5.2, in terms of *human factors* regarding awkward postures in Prunet et al. (2024) Section 5.3, and in terms of *mathematical optimization* for using threshold constraints in Section 7.2. Then, future research directions are discussed in both parts of the work. Note that, in the current paper (first part), we often refer to human-aware models without a proper explanation of the related concepts. The interested reader is referred to the second part (Prunet et al., 2024) to get this information.

1. Introduction

Operations Research (OR) has been historically focused on economic considerations, reflecting the concerns present in the industry. With the globalization of the economy, the increasing level of competition and demand customization have led to growing economic pressure on decision-makers. This pressure has been particularly high in the logistics and manufacturing fields to reduce costs and improve the efficiency of operations, quality of services, and system agility. The concomitant development of data-driven optimization of operations, applied to a large variety of complex industrial problems, has shaped the current landscape of OR. The advance in the accessibility to computing power allows us to consider and successfully treat more complex problems that do not limit their scope to economic considerations. In this sense, additional topical considerations have begun to appear in decision models after the early 2000s, following a more global societal shift, where ecological and social responsibility is more and more accounted for by decision-makers, as growing pressure from stakeholders. This trend is illustrated by the rise of two related paradigms namely, sustainable development, and Industry 5.0, presented in the following paragraphs.

Sustainable development. This concept is increasingly becoming a major paradigm that reframes the global strategy of companies and organizations. The concept is defined as "*the development that meets the need of the present without compromising the ability of future generations to meet their own needs*" (Keeble, 1988). The main idea of this paradigm is to consider social and environmental indicators together with economic ones when considering business decisions and performance assessments. The three pillars of sustainable development, namely economic, environmental, and social, are considered on the same level of importance, explaining the increasing concerns toward the social responsibility of companies. *Decent working conditions* is actually one of the 17 sustainable development goals, that constitute the 2030 Agenda of sustainable development ratified by the United Nations in 2015.[1] According to the International Labour Organization

[1] The resolution A/RES/70/1 of the seventieth general assembly of the United Nations of 21 October 2015 on the 2030 Agenda of sustainable development. https://sdgs.un.org/2030agenda Access: September 20, 2022.

(ILO)[2] and the World Health Organization (WHO),[3] over 2.3 million people die yearly from work-related causes (Takala et al., 2014). Studies show that, at any given time, 20% of employed adults suffer from Work-related Musculoskeletal Disorders (WMSD) (Vézina et al., 2011). Furthermore, from an economic perspective, the direct and indirect costs of work-related injuries are estimated at 4% of the world GDP (Takala et al., 2014). Therefore, the improvement of working conditions and the reduction of work-related health problems are still an important challenge worldwide.

Industry 5.0. This is an emerging concept referring to a change of paradigm in the organization of logistics and manufacturing systems, which are the focus of the present work. Industry 5.0 proposes a shift from a system-centric vision to a human-centric vision of industrial systems, by placing the role and well-being of operators at the center of the process design (Lu et al., 2022). Sustainability and resilience are the two other pillars of Industry 5.0. The consideration of human factors, at physical, cognitive, perceptual, and psychosocial levels, is especially relevant in logistics and manufacturing fields, especially considering the development of human–machine interactions (Wang et al., 2017), or the aging of the working population (Calzavara et al., 2020).

The need to account for human factors in decision support models for logistics and manufacturing systems will continue to gain importance in the near future. Two arguments support this claim:

- **Regulatory aspect:** Companies in the logistics and manufacturing sectors still rely heavily on manual labor, especially for tasks requiring a high degree of precision and flexibility. This is, for example, the case for truck drivers in logistics, order pickers in warehousing (Grosse et al., 2015b), or assembly line operators (Battini et al., 2016a). Furthermore, these jobs can account for a high level of physical and cognitive stress, repetitive movements, lifting tasks, and awkward positions. The increasing demand for social accountability of companies has led to a growing number of laws regulating the working conditions in the industry. In logistics, the European regulation EC 561/2006[4] and the American Hours of Service of Drivers regulation[5] both propose a framework to regulate the driving and working times of truck drivers. The manufacturing sector has also been subject to numerous regulations aimed at reducing ergonomic risks in workplaces. Among others, one can cite the Directive No. 2006/42/EC of the European Parliament on machinery usage,[6] the Directive No. 89/391/EEC on general measures to encourage improvements in safety and health of workers,[7] or the Occupational Safety and Health Act of 1970.[8] Furthermore, several ergonomics standards have been developed by the International Organization for Standardization and the European Committee on Standardization to design production systems. Dul et al. (2004) listed up to 174 international ergonomic standards for production systems, going from general recommendations on the design of processes to specific requirements for manual handling, human–computer interactions, mental load, noise, heat, etc. Therefore, planning models increasingly need to account for human factors in order produce industrially coherent solutions.
- **Integration aspect:** The second driver of the relevance of human considerations in logistics and manufacturing refers to the modeling of human characteristics and behaviors. Several empirical studies have identified a clear link between the ergonomic burden and individual performance in the industry (see e.g., Shikdar and Sawaqed (2003), Erdinç and Yeow (2011) and Ivarsson and Eek (2016)). In addition to poor ergonomic conditions, numerous other factors can impact the productivity of employees. These include fatigue (Yung et al., 2020), noise exposure (Szalma and Hancock, 2011), individual learning (Grosse et al., 2015a), stress and psychosocial factors (Halkos and Bousinakis, 2010), etc. Overall, the study of human factors is essential to understand and model the productivity of employees accurately. Logistics and manufacturing are heavily relying on the optimization of their operations, it is, therefore, crucial to model as accurately as possible the duration of the operations. This will gain even more importance with the spread of the Industry 5.0 paradigm. Oriented toward process automation, human–robot collaboration is becoming more common in production systems, where human operators and robots work on the same workstations. A thorough comprehension of the modeling of human characteristics is crucial for the success of such systems (Wang et al., 2017).

From an academic perspective, the issue of improving working conditions has been mainly tackled by Human Factors and Ergonomics (HF/E), as a human-centered scientific discipline aiming at a better understanding of the interactions between human operators and production or service systems (see Section 2). HF/E lies at the interface between psychology, anthropometry, physiology, mechanics, design, and engineering (Bridger, 2018). This inter-disciplinarity results in a variety of methods used to evaluate work situations, from observational methods to statistics, passing by biomechanics, system theory, epidemiology, and occupational medicine. A number of these methods are presented in the second part (Prunet et al., 2024) of this review. However, OR and mathematical programming have not been part of the ergonomist toolbox until the beginning of the 21st century. To our best knowledge, the pioneering work of Carnahan et al. (2000) was the first to use OR as a tool for ergonomic purposes to optimize a job rotation schedule (see Section 6.1.1).

In the OR literature, economic considerations have historically been largely dominant (Dekker et al., 2012). However, other trends have emerged recently. Ecological considerations have made their way into the optimization literature, e.g., with green logistics (Dekker et al., 2012; Sbihi and Eglese, 2010), sustainable manufacturing operations scheduling (Giret et al., 2015) or circular economy in production planning (Suzanne et al., 2020). Human-aware considerations have also been considered for a couple of decades, from different perspectives, with different degrees of modeling accuracy. It is, however, still a maturing topic that can be difficult to get a grasp of for a newcomer, addressed by different research communities within OR via various approaches. Human factors are hence quite challenging to integrate into existing optimization models for several reasons:

- *At the problem statement level:* Given an industrial situation, identifying the most relevant human factors to consider is challenging without sufficient field experience.
- *At the modeling level:* Once the relevant factors are identified, it is neither easy nor obvious to propose appropriate quantitative modeling.

[2] Database on labour statistics of The International Labour Organization. https://ilostat.ilo.org/ Access: September 20, 2022.

[3] World Health Organization Mortality Database. https://www.who.int/data/data-collection-tools/who-mortality-database Access: September 20, 2022.

[4] The European Community (EC) regulation No 561/2006 of 15 March 2006 on machine work. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32006R0561 Access: September 20, 2022.

[5] The Federal Motor Carrier Safety Administration regulation No. 49 CFR Parts 385, 386, 390 and 395 about Hours of Service of Drivers. https://www.govinfo.gov/content/pkg/FR-2011-12-27/pdf/2011-32696.pdf Access: September 20, 2022.

[6] The Directive No. 2006/42/EC of the European Parliament and of the Council of 17 May 2006 on machinery usage. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32006L0042 Access: September 20, 2022.

[7] The European Council Directive No. 89/391/EEC of 12 June 1989 on the introduction of measures to encourage improvements in the safety and health of workers at work. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A31989L0391 Access: September 20, 2022.

[8] The Occupational Safety and Health Act of 1970 https://www.osha.gov/laws-regs/oshact/completeoshact Access: September 20, 2022.

- *At the instance level:* The data collection on this part often requires extensive field observations and measurements, or dedicated lab studies.
- *At the solution level:* The integration of human considerations often has a significant impact on problem complexity. Tools and frameworks commonly used in the HF/E community do not usually have convenient mathematical properties such as linearity or convexity.

This review aims at bridging the understanding gap of OR academics and practitioners about HF/E methods, and at providing them with a broad understanding of the related problems, by presenting the models, methods, and tools used in the literature to design human-aware optimization methods for logistics and manufacturing systems.

Due to the length of the manuscript, the present work is divided into two separate papers. After the scope delineation, the first part of this review (the current paper) conducts a quantitative and thematic analysis of the retrieved corpus according to a semi-systematic methodology. Section 2 provides the related background of the present work with respect to the existing literature and defines clearly the scope of the review. Section 3 presents the search methodology used for the material collection. Sections 4 to 6 give an overview of the retrieved literature corpus structured by class of problems encountered in logistics and manufacturing systems, namely: logistics (warehousing and vehicle routing), production systems (production scheduling, assembly line balancing, production planning, and system design), and workforce-related problems (workforce scheduling and management). Section 7 is specially dedicated to investigating the impact of human-aware considerations on mathematical models. Particular attention is put on the features added to an optimization model (e.g., new constraints, modification of the objective function) to account for the human factors, and the impact on solution methods. Section 8 discusses the main finding of this first part, and proposes research directions. Finally, Section 9 concludes this first part of the review. In the second part of this work (Prunet et al., 2024), the focus is set on the modeling of human characteristics. The different modeling constructs found in the related literature are presented and contextualized. Prunet et al. (2024) has been written with the idea of being used as a survey of the different modeling of human factors for interested academics and practitioners.

2. Terminology, related background, scope, and motivations

In this section, the present review is put in context and motivated with respect to the literature. First, we propose comprehensive definitions of the human-related key concepts used throughout this work. Then we survey and synthesize our findings from the existing related reviews. From this analysis, we propose a clear delineation of the scope of this review.

2.1. Definitions of human-related key concepts

In the OR literature, the key terms related to human-aware optimization are found with various definitions and interpretations, the most prominent one being the term *human factors*. A naive interpretation from an OR practitioner would define it as any characteristic or behavior related to the human nature of employees. However, *Human Factors and Ergonomics* also refers to a scientific discipline, defined as follows by the International Ergonomics Association[9]:

> Ergonomics (or human factors) is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimize human well-being and overall system performance. The terms ergonomics and human factors are often used interchangeably or as a unit (e.g., human factors/ergonomics – HF/E or E/HF), a practice that is adopted by the IEA.

As the topic of this review is prone to cross-disciplinary work, we stress the importance of avoiding the confusion between human factors and HF/E to facilitate mutual comprehension between researchers with different backgrounds. Interested readers can find a more thorough definition and explanations on HF/E in Wogalter et al. (1998). Starting from this clarification, let us adopt the following convention for the remainder of this paper:

- **Human Factors and Ergonomics (HF/E)**: as a scientific discipline that studies the interactions between a human operator and his/her work system, emphasizing the improvement of working conditions. HF/E research frameworks usually identify four critical elements in human–system interactions: *physical* related to the human body, *mental* related to the task cognitive complexity, *perceptual* related to the human perceptions (e.g., hearing, sight, etc.) and *psychosocial* related to the interactions with colleagues and management (Salvendy and St, 2022).
- **Operations Research (OR)**: as a scientific discipline that aims at providing better decisions by the analysis and modeling of complex systems, and the development of efficient decision-support algorithms based on advanced mathematical methods. A typical OR work involves optimizing the performances of a work system through the following steps: *1.* the observation and analysis of a work environment, *2.* the development of a simplified mathematical model for this environment, *3.* the design of an efficient algorithm to solve the problem, and *4.* the industrial evaluation of the returned solution.
- **Work-related Musculoskeletal Disorder (WMSD)**: as an injury or a disease that affects the body's structural systems (i.e., the bones, tissues, nervous or circulatory systems), caused by a work situation. Examples of WMSDs include (but are not limited to) low back pain, carpal tunnel syndrome, tendinitis, or trigger finger. WMSDs encompass a large portion of work-related injuries, but some do not affect the musculoskeletal system (e.g., hearing loss, excessive heat exposure).
- **Ergonomic Risk (ER)**: referring to the additional risk factor of developing WMSD, or any other occupational accident, disease, or injury, for an employee due to a specific work situation. This concept is found under different names in the literature, without a clear difference: ergonomic load, ergonomic workload, ergonomic burden, ergonomic strain, etc.
- **Risk Factors**: as workplace situations that cause wear and tear for the body, and increase the ergonomic risk for employees. These include repetition, awkward posture, lifting, noise, work stress, etc.
- A **Human Factor (HF)**: as a characteristic or behavior typically human. This can be a factor affecting the individual performance of workers and the ability to perform tasks (e.g., fatigue, learning, forgetting), the safety of workers (e.g., work-related injuries, awkward postures), the interests of workers (e.g., satisfaction, motivation), or any other real-life human characteristic interacting with the optimization of a production or service system.
- A **Human-Aware Model (HAM)**: as a quantitative model that explicitly translates a HF into a mathematical expression, which can, in turn, be used in an optimization problem (e.g., in a constraint or as an objective function). In other terms, the concept of HAM is the transposition of HF/E methods into an OR

[9] The International Ergonomics Association (IEA). https://iea.cc/what-is-ergonomics/ Access: September 20, 2022.

context. A typical HAM can be expressed as a function mapping the different states of a human–system to a set of real numbers, which can be interpreted as the "ergonomic score" of the states. For instance, the NIOSH equation is a HAM that evaluates the ergonomic risk related to manual handling. Based on a set of criteria (e.g., weight, handling posture, duration), a score can be computed for each handling task that needs to be scheduled in a shift and used as input for a related optimization problem.

2.2. Previous reviews

The integration of a HF in optimization problems is a broad subject. As such, several reviews/surveys have been published on the topic. However, these works often focus on a single topic of logistics and manufacturing, yet with a scope broader than pure optimization problems, i.e., including material from other disciplines, such as industrial engineering or HF/E. In this section, a brief overview of the most relevant reviews is provided.

- **Warehousing:** (Grosse et al., 2015b, 2017b) study the integration of HFs in order picking (i.e., the action of retrieving, or "picking", items from the storage area to prepare orders) models. Grosse et al. (2017b) perform a content analysis of the retrieved literature, and thus give a broad overview of the topics of interest and related trends. With a tighter scope, Grosse et al. (2015b) place the emphasis on planning models in order picking, by presenting a systematic methodology and introducing a new conceptual framework and taxonomy to classify and analyze this research stream. De Lombaert et al. (2022) study human aspects in the scope of order picking planning models, with a focus on the integration into mathematical models and insights from semi-structured interviews of practitioners.
- **Vehicle routing problem:** Vega-Mejía et al. (2019) review the VRP with triple bottom line sustainable objectives, one of those being social. However, the paper focuses more on economic and ecological aspects, as they are more representative of their review corpus, the social aspect only being briefly discussed. Matl et al. (2018) propose a review on workload equity in the VRP and provide an in-depth analysis on the topic.
- **Production scheduling:** As reflected by the reviews on the topic, the scheduling community has been quite prolific in the consideration of HFs into their mathematical models. The reader is referred to Lodree et al. (2009) for a general narrative review about Human-Aware Modeling in the scheduling domain. Lodree et al. (2009) deal with works on the topic published prior to 2007, including both OR-related and empirical HF/E studies, and provide an insightful analysis and a modeling framework on the sequencing of human tasks. The introduction of learning aspects has also been extensively studied by the scheduling community, from the early works on learning in management science to the most recent development of this stream. Biskup (2008) provides a review on scheduling integrating learning jointly with a relevant analysis of the practical aspects of learning, as well as a discussion on the mathematical implications of the different ways to model such effects. Azzouz et al. (2018) present an update of the review of Biskup (2008), and propose a taxonomy and a classification framework to map the related areas of the prolific stream of scheduling with learning effects. From an OR perspective, Cheng et al. (2004) present a short survey on the mathematical implications of time-dependent processing times on scheduling models.
- **Assembly lines:** Assembly lines are also a well-established research topic for human-aware optimization, due to the inherent balance of the workload between workers, which can be seen as a balance of the ER. Otto and Battaia (2017) propose a systematic review on line balancing and job rotation to reduce the physical ER in assembly. The authors provide an analysis of both the HAMs available for assembly line practitioners, and the mathematical perspective of integrating such considerations in existing models. Albeit not a review paper, Peltokorpi et al. (2014) provides a network analysis of the different performance factors for assembly lines.
- **Lot sizing:** Jaber et al. (2022) review the integration of learning curves in lot sizing models. The focus is put on the different learning curve models and how they are integrated into the models. The results are presented chronologically to highlight the development of the field.
- **Workforce planning:** This class of problems has also been studied, especially with skill considerations. De Bruecker et al. (2015) present a state-of-the-art review on workforce planning with skills, focusing on both mathematical modeling and managerial implications. The authors also propose a new taxonomy for this research stream, based on what skills are exactly modeling, and how they are integrated into decision models. Their taxonomy constitutes the basis of our analysis of skills in (Prunet et al. (2024), *Skills*). Xu and Hall (2021) study fatigue in workforce scheduling in a broad sense. They focus on the work-rest scheduling and shift scheduling problems accounting for human fatigue and derive insights from empirical studies and opportunities for OR applications.
- **Reviews focusing on specific HFs:** Several works review the literature focusing on a given HF instead of an area of logistics and manufacturing. Karsu and Morton (2015) survey the issue of equity in OR models with an emphasis on the modeling implications. Anzanello and Fogliatto (2011) provide a narrative review on learning curves, with a focus on mathematical models. Glock et al. (2019b) propose a systematic review on the applications of leaning curves in operations management, and Grosse et al. (2015a) performed a meta-analysis of empirical studies on the use of learning curves in a production context. Katiraee et al. (2021) review the literature modeling heterogeneously the workforce in production systems. Finally, several reviews study the integration of HFs in logistics and manufacturing systems with an HF/E point of view, without considering mathematical models: Padula et al. (2017) on job rotation to prevent WMSD, Kolus et al. (2018) on human errors and their implications, Jahanmahin et al. (2022a) on human–robot collaboration, and Muhs et al. (2018) on the temporal variability of tasks performed by a human operator.

To conclude, one can see that the integration of HFs in the optimization of logistics and manufacturing systems are extensively studied and reviewed. However, most of these reviews focus either on a single topic, or they conduct the study only through an OR or HF/E perspective, thus giving a restricted view of this interdisciplinary topic. In the present paper, we aim at broadening the scope to give a general picture and a more holistic analysis of the subject, that has not been done previously in the literature. In that sense, the present work can be seen as an extension of previous works on HF an operations management (Larco Martinelli, 2010; Neumann and Dul, 2010), but with a clear focus on optimization. Grosse et al. (2017a) provide a first attempt at such a work, yet the restricted length of the paper does not allow the authors to provide an in-depth analysis.

2.3. Scope

The present work aims at surveying the research stream dedicated to the integration of HF in the optimization of logistics and manufacturing systems. As a consequence, to be relevant for this work, a paper must deal with:

I. Optimization. Despite being at the interface between several disciplines, we chose to review only the papers presenting an optimization model, either explicitly or implicitly, but clearly defined.

II. logistics or manufacturing. According to the Cambridge Business English Dictionary (Press, 2011), logistics and manufacturing are defined as follows:

Logistics: The process of planning and organizing to make sure that resources are in the places where they are needed so that an activity or process happens effectively.

Manufacturing: The business of producing goods in large numbers, especially in factories.

These definitions cover the classical topics of OR, including planning and scheduling, when applied to a production process. However, other side activities enabling manufacturing to be processed, effectively and efficiently, are also covered by these definitions, namely: inventory management, warehousing, vehicle routing, and lot sizing operations.

III. Human factors. We consider that a paper fits in the scope if it considers the modeling of a HF or deals with the improvement of the employees' welfare.

2.4. Motivations

The research stream on human-aware optimization in logistics and manufacturing systems is consistently growing. However, the related topics are studied through the lens of a specific field of application, or a specific human factor. The main goal of this paper is to fill this gap by providing a holistic picture of this broad topic, and a coherent analysis of the research stream. The second objective is to propose to interested practitioners a comprehensive overview of the available models to represent and quantify human characteristics, both from the HF/E and OR perspectives. These goals are expressed through the following research questions addressed throughout both the current paper and the second part of the work (Prunet et al., 2024):

- Which HFs are studied in the related literature, and in which logistics and manufacturing areas are they present?
- How are HFs modeled in the related literature, and which HAMs are available to take them into account?
- How are HAMs integrated into optimization models, and how does their integration impact the models from a mathematical programming perspective?

The two parts of the work are intended as a "guidance-type" presentation of human-aware optimization, to help researchers at identifying relevant human factors for their problems, appropriate quantitative models for these factors, and references to further theoretical and applied works on the topic.

3. Methodology

3.1. Material collection methodology

This section presents the methodology followed to collect the material for this review. The most common types of methodological approaches used to perform a literature review are: systematic, semi-systematic, narrative, integrative, and meta-analysis (Snyder, 2019). Motivated by the large number of papers fitting the scope defined in Section 2.3, we opt for a semi-systematic methodology. In short, the search methodology is systematic, to ensure that all relevant topics are covered by the review. However, the amount of material does not realistically allow a systematic analysis of every in-scope work, and thus the analysis and writing are narrative. This means that for some topics (specifically, papers dealing with skills and/or learning), the decision to include them in scope is made at the discretion of the authors. The reader interested in systematic reviews on specific topics is referred to Section 2.2. Nevertheless, one should note that, even though a number of papers are excluded, the systematic search methodology ensures that all relevant topics and modeling approaches are covered in this paper. With the same philosophy, we highlight that the length of a given section does not necessarily reflect the bibliometric importance of the covered topic.

Table 1
List of keywords in the search string.

Logistics and manufacturing		Human-aware modeling
warehous*, storage, pick*, batch*, assembly, production, "lot sizing", manufactur*, planning, routing, logistic*, schedul*, maritime	AND	musculoskeletal, welfare, postur*, lift*, "human factor*", ergonomic*, "human error*", "learning curve", "learning effect", "forgetting", "human learning", pain, noise, bored*, fatigue, break, rest, cognitive, equity, safe, discomfort, turnover, absenteeism, vibration, repetit*, injury, "social benefit*", skill*, psychosocial, "workload smoothing"

The material is collected using Scopus and Web of Science databases, by applying the following set of rules and selection criteria (SC):

- According to the scope of this review, two sets of keywords are created, one for *logistics and manufacturing*, and one for *human-aware modeling*. A search query is created for the databases with one word from each of the two sets, presented in Table 1. Following a preparatory scan of the literature, the list of keywords has been created at the discretion of the authors with the objective of covering as many scientific works as possible dealing with Human-Aware Logistics and Manufacturing Systems.
- Only papers published in English are considered.
- All publication dates are considered up to 2022.
- (SC1) A category filter is applied on both databases to target the relevant papers. On Scopus, the search is limited to *Computer Science* and *Decision Science* categories. On Web of Science, the following categories are considered: *Computer Science (Theory methods, artificial intelligence & interdisciplinary applications)*, *Operations research and management science*, *Engineering Industrial*, *Management*, *Transportation*, *Transportation science technology* & *Mathematics interdisciplinary applications*.
- (SC2) Only articles published in journals and book chapters are considered. Conference proceedings are excluded from this study in order to keep the size of the studied corpus manageable.
- (SC3) From the collected list of papers, duplicates are removed, and we only retain the works that satisfy the following three conditions based on their title, keywords, and abstract, in accordance with what is presented in Section 2.3:
  1. The paper provides an optimization mathematical model, or an optimization solution method.
  2. The paper explicitly considers Human-Aware Modeling in its title, abstract, or keywords. The mention of HF or social welfare is explicit. Moreover, these aspects are explicitly modeled.
  3. The paper deals with logistics or manufacturing.

  As a result, a total of 844 papers are retrieved after the application of (SC3).
- (SC4) After a thorough reading, only relevant papers are included. Studies dealing with *skills* and *learning* include a lot of papers, and we decided to exclude some of them. Even if the exclusion process is not reproducible, the following guidelines are applied for the paper selection:
  1. Papers falling in the scope of the review and focusing their contribution on Human-Aware Modeling are systematically included. This ensures that every relevant assessment or

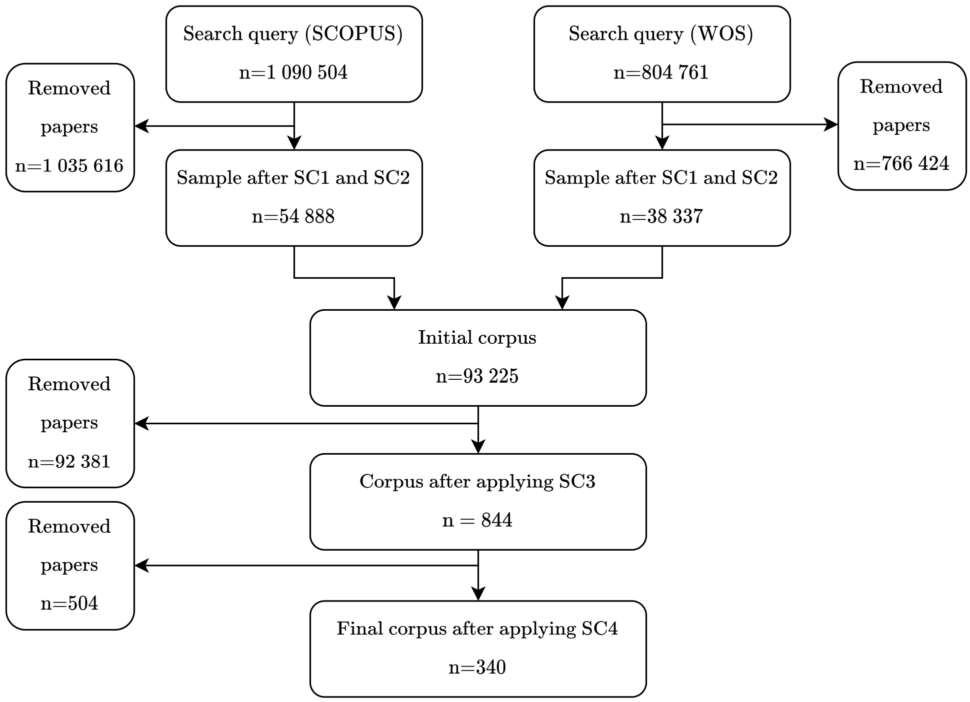

Fig. 1. Prisma flow diagram of the literature search and inclusion process.

modeling approach found in the literature is addressed by the present review.

2. Papers focusing their research contributions on the algorithmic side, and using a basic *ad hoc* HAM are more likely to be excluded. For example, when tackling the topic related to *skills*, the majority of papers use a simple constraint to impose the compatibility between tasks to schedule and workers that are allowed to perform them. Despite its vast use, this simple HAM presents a limited interest in the scope of this review, thus most of the papers proposing it are not included.

After applying (SC4), 504 papers are excluded. The final corpus thus includes 340 papers, which are studied and discussed in the current work.

Fig. 1 displays the flow of the selection process. The value of n represents the number of papers resulting from the corresponding search.

Structure of the paper. Sections 4–6 provide a presentation of the collected material, decomposed by field of application within logistics and manufacturing. Three main areas of application are identified: *logistics systems*, *manufacturing systems*, and *workforce-related problems* that could be applied in various contexts. Each section is then decomposed into specific subsections. Note that this structure aims at easing the reading, by decomposing the presentation of the collected material into sections of similar length. Note that we do not aim at introducing a consistent classification of the field. An inductive approach has been used for the classification: studies are clustered based on the similarity of the problem studied in terms of field of application, time horizon, main decision variables, and problem structure. Therefore an overlap is present among some sections, and some works could be classified into several categories. However, we decided to include each paper in a single section, where it seemed the most relevant. The taxonomy applied in different sections relies on previous literature studies when available, for example, the work of Lodree et al. (2009) for workforce scheduling problems.

3.2. Summary tables: Format and convention

The collected material is presented through summary tables in the next sections. To facilitate navigation, the tables' entries refer to the sections of both this paper and the second part (Prunet et al., 2024). The tables contain the following columns:

- **Reference:** The reference of the paper in the bibliography.
- **Case study:** This column indicates if the work is applied to a real-life case study.
- **Modeling:** This column specifies how the HAM used in the paper is integrated into the optimization model. The different options correspond to the subsections of Section 7, and include *MO* for true multi-objective, *MO-He* for a heterogeneous aggregation of several objective functions, *MO-Ho* for a homogeneous aggregation of several objectives, and *SO* for a single objective function. Concerning the constraints, *CC* is used for compatibility constraints, *TC* for threshold constraints, *TWC* for time window constraints, *FSC* for forbidden sequence constraints, and *FBC* for forward–backward constraints. Concerning the data, *VTT* designates a variable task time, and *VQ* a variable quality.
- **Heterogeneous workforce (HW):** This column is dedicated to the modeling of the workforce. More precisely, we check if the workforce is modeled heterogeneously or not, i.e., if different employees are modeled with different characteristics, or if they are all interchangeable. If the modeling is heterogeneous, this column specifies which parameter is a defining characteristic of an employee. The range of options includes the skills *S*, the learning rate *LR*, physical properties *PP*, cognitive and psychosocial properties *CPP*, and preferences *P*.
- **HAM:** This column indicates the quantitative model used in the paper to represent the considered human factor. The identified options correspond to the sections of the second part of this review (Prunet et al., 2024).

Table 2
Warehousing references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Const.	Param.	HW	HAM
Marvel et al. (2001)	✓		CC			Handling
Hwang et al. (2003)		SO				Biomechanical
Grosse et al. (2013)				VTT	LR	Learning
Grosse and Glock (2015)				VTT	LR	Learning
Battini et al. (2016b)		MO				EE, RA
Calzavara et al. (2017)		MO				EE
Otto et al. (2017)		SO				Handling
Battini et al. (2017b)	✓				S	Posture, RA
Al-Araidah et al. (2017)						Visual, anthropometric
Larco et al. (2017)	✓	MO				Expert collaboration
Matusiak et al. (2017)	✓			VTT	S	Skills
Hong (2018)				VTT	S	Skills
Diefenbach and Glock (2019)		MO				EE
Glock et al. (2019a)	✓	MO				Biomechanical
Calzavara et al. (2019a)	✓	MO				EE, posture
Zhang et al. (2019a)	✓			VTT	PP, LR	Skills, learning
Kudelska and Pawłowski (2020)		MO				Implicit
Gajsek et al. (2021)	✓	MO-He				EE, posture
Feng and Hu (2021)	✓			VTT	S	Skills, fatigue effect
Gajšek et al. (2021)		MO				EE, posture
Kapou et al. (2022)	✓	MO-He	CC			Handling
Mou (2022)		MO		VTT	S	Skills, learning, equity

4. Logistics systems

4.1. Warehousing

Warehousing activities, and especially order picking, still heavily rely on manual labor (de Koster et al., 2007), and the work can be physically demanding. The integration of HFs into mathematical models has therefore gained attention from OR researchers on this topic, as presented in Table 2. In this context the most common HFs are the *risk of WMSDs*, employees *learning*, and *fatigue*. An interested reader is referred to Grosse et al. (2015b) and De Lombaert et al. (2022) for dedicated reviews on the topic.

WMSD risk assessment. An order picker is subject to various risk factors for WMSDs linked to the material handling activity, especially the frequent lifting of products (Otto et al., 2017; Kapou et al., 2022), and the awkward postures required to perform the picks, both for the hand/wrist and the entire body (Al-Araidah et al., 2017; Glock et al., 2019a; Calzavara et al., 2019a). Studies aim at mitigating this risk at different levels of decisions. First, regarding the design of the picking area layout, there is the possibility of rotating the pallets to enable easier access to the stored items (Glock et al., 2019a; Calzavara et al., 2019a) use the OWAS method to evaluate different situations. The optimization of the storage decisions also plays an important role in ER of the operators. Otto et al. (2017) integrate storage and zoning decisions to balance the ER among employees, and Kudelska and Pawłowski (2020) study the impact of storage decisions using simulation. The picker routing decisions are studied, for example, by Al-Araidah et al. (2017) with the goal of clustering the items so that the picker (on a vehicle) can safely pick several products.

Learning. Grosse et al. (2013) and Grosse and Glock (2015) study the impact of employee learning and forgetting on storage assignment and reassignment decisions in the warehouse. The topic has been applied to omni-channel supermarkets, where the order picking is integrated with batching or delivery decisions (Zhang et al., 2019a; Mou, 2022).

Fatigue with energy expenditure. Due to the variety of elementary tasks performed by a picker (e.g., walking, picking, pushing a trolley), a holistic HAM such as energy expenditure is suited to the context. Calzavara et al. (2017) and Calzavara et al. (2019a) use the energy expenditure in their models to integrate the choice of picking from a full pallet, or from half pallets on the floor and upper shelves, balancing efficiency and ER. This HAM is often considered when optimizing the storage decisions, where an ergonomic objective is used on top of the classical picking efficiency optimization (Battini et al., 2016b; Diefenbach and Glock, 2019; Gajsek et al., 2021; Gajšek et al., 2021).

Other HFs. Larco et al. (2017) use a regression from a worker opinion survey on the discomfort of the picking operations in different situations as an input to their model, and Matusiak et al. (2017) conduct a regression analysis from historical data to determine the different skills and skill levels of the employees. Workload equity among pickers is also considered (Mou, 2022).

4.2. Vehicle routing

The Vehicle Routing Problem (VRP) and its extensions represent an important class of problems studied in the OR literature, where the aim is to assign a set of customer visits to vehicles while optimizing the total traveled distance. Table 3 presents the works on the VRP in the scope of this review. Two main HFs are studied in VRP: the fatigue of drivers, and the equity between them. The topic of drivers' fatigue is tackled either from a regulation perspective, with the *Hours of Service (HOS) regulations*, or with an approach focused on rest breaks.

Fatigue with HOS regulations. Recent regulations enforce the explicit scheduling of rest breaks in routing plans for logistics providers (see Prunet et al. (2024), *Regulatory breaks*). These HOS regulations lead to the development of VRP works on the topic. These works aim at optimizing a routing plan that is valid for classical VRP constraints (e.g., capacity, time windows), while respecting the HOS regulations on drivers working and driving times. The starting time and duration of the rest breaks are introduced as new decisions to be scheduled in the model. This makes the problem more challenging (see Section 7.2 on forward–backward constraints). HOS regulations have been rigorously introduced for the VRP by the seminal work of Goel (2009), although some earlier works deal with the breaks scheduling aspect via less sophisticated methods (Brandao and Mercer, 1997). Recent works on this problem may include additional considerations, such as driver well-being (Rancourt and Paquette, 2014; Khaitan et al., 2022), green objectives (Zarouk et al., 2022; Dukkanci et al., 2022) or real-life side constraints (Goel et al., 2021).

Fatigue with rest breaks. The scheduling of driver breaks has also been considered in the VRP without relying on actual regulation frameworks. A common consideration is the scheduling of a *meal break* in the routing plan, to enable drivers to get a full break during their shift. This HAM

Table 3
Vehicle routing references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Const.	Param.	HW	HAM
Brandao and Mercer (1997)			FBC			HOS regulations
Kim et al. (2006)	✓	MO-He	TWC			Meal breaks, equity
Erera et al. (2008)			FBC			HOS regulations
Goel (2009)			FBC			HOS regulations
Ceselli et al. (2009)			FBC			HOS regulations
Benjamin and Beasley (2010)			TC, TWC			Meal breaks
Kok et al. (2010b)			FBC			HOS regulations
Kok et al. (2010a)			FBC			HOS regulations
Prescott-Gagnon et al. (2010)			FBC			HOS regulations
Wen et al. (2011)	✓		FBC		S	HOS regulations
Goel (2012)			FBC			HOS regulations
Melton and Ingalls (2012)		MO-Ho				Psychosocial
Hollis and Green (2012)	✓	MO-He	TWC			Visual, meal breaks
Rancourt et al. (2013)			FBC			Regulation breaks, psychosocial
Rancourt and Paquette (2014)	✓	MO	FBC			HOS regulations
Goel and Vidal (2014)			FBC			HOS regulations
Rattanamanee et al. (2015)		SO	TC		PP	EE
El Hachemi et al. (2015)	✓		TWC			Meal breaks
Battini et al. (2015)	✓			VTT	LR	Learning
Min and Melachrinoudis (2016)			FBC			HOS regulations
Coelho et al. (2016)			TWC			Meal breaks
Liu (2016)		MO-He				Equity
Bowden and Ragsdale (2018)			TC			HOS regulations
Mathlouthi et al. (2018)			CC, TWC		S	Skills, meal breaks
von Elmbach et al. (2019)		SO				Handling
Yan et al. (2019)				VTT	S	Skills, fatigue effect
Matl et al. (2019)		MO				Equity
Lehuédé et al. (2020)		MO				Equity
Kandakoglu et al. (2020)	✓	MO-He	CC, TWC		S	Meal break, equity, skills
Rabbani et al. (2020)		MO				Equity
Mayerle et al. (2020)			TWC, FBC			HOS regulations
Anoshkina and Meisel (2020)		MO-He	CC		S	Skills, psychosocial
Ulmer et al. (2020)		MO		VTT	S, CPP	Learning
Vital and Hsieh (2021)			FBC			HOS regulations
Bakker et al. (2021)	✓			VTT		Learning
Haitam et al. (2021)			TWC			Meal breaks
Goel et al. (2021)			FBC			HOS regulations
Zarouk et al. (2022)			FBC			HOS regulations
Sartori et al. (2022)			FBC			HOS regulations
De Genaro Chiroli et al. (2022)			TWC, FBC			HOS regulations
Fu and Ma (2022)	✓		TC			EE
Dukkanci et al. (2022)		MO				Equity
Eskandarzadeh and Fahimnia (2022)			FBC			HOS regulations
Xu et al. (2022)			FBC			HOS regulations
Khaitan et al. (2022)		MO	FBC			HOS regulations, satisfaction
Li et al. (2022)		MO				Equity

is often modeled with time window constraints, in which the break must be scheduled (Kim et al., 2006; Benjamin and Beasley, 2010; Coelho et al., 2016; Kandakoglu et al., 2020). Driver fatigue and rest breaks have also been considered with other HAMs that are worth mentioning. In Bowden and Ragsdale (2018) and Fu and Ma (2022), fatigue is modeled based on biomathematical approaches as a lack of alertness and increased sleepiness. Service times at customer locations are modeled as dependent on the fatigue level of the employee in Yan et al. (2019).

Equity. Workload equity has been a growing trend in VRP in the last years, focusing on the drivers' workload as it is reviewed in the present work, as well as a general balance of the available resources (Matl et al., 2018). In the corpus, an equity objective is often included in studies focusing on real-life applications, such as nurse visit routing and scheduling (Kandakoglu et al., 2020) or waste collection problems (Kim et al., 2006; Rabbani et al., 2020). From a more general perspective, Matl et al. (2019) compare different equity functions for the VRP, and assess the impact on the solution depending on which resource is balanced among drivers: number of visited customers, traveled distance, load handled, etc.

Other HFs. Additional topics of interest found in the VRP literature include the familiarity of drivers with the routes they are assigned to, where the driving/processing times decrease if one driver is familiar with the itinerary and/or customer locations. This is modeled using either an exogenous parameter for each driver (Ulmer et al., 2020), or more dynamically with learning curves (Battini et al., 2015; Bakker et al., 2021). Anoshkina and Meisel (2020) study the intraday and interday technician routing, accounting for skills and team consistency. Khaitan et al. (2022) account for the driver well-being, modeled by fuzzy reasoning based on natural language processing of the corresponding studies.

5. Manufacturing systems

5.1. Production scheduling

The general definition of production and machine scheduling is very broad (Chen et al., 1998), and can fit a large class of problems. In this section, we consider scheduling problems where the main decisions are the assignment and sequencing of a set of jobs on a set of machines. This differs from the other sections dealing with scheduling problems, where the main decision is the scheduling of human operators' activities. In this case, the HFs are indirectly accounted for in optimization models, since they are not intrinsically represented by the decision variables. Existing studies, presented in Table 4, mainly

Table 4
Production scheduling references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Modeling Const.	Modeling Param.	HW	HAM
Biskup (1999)				VTT		Learning
Cheng and Wang (2000)				VTT		Learning
Mosheiov (2001)				VTT		Learning
Mosheiov and Sidney (2003)				VTT		Learning
Wang and Xia (2005)				VTT		Learning
Tang et al. (2006)	✓			VTT, VQ	S	Skills
Wang (2007)				VTT		Learning
Wu and Lee (2008)				VTT		Learning
Aravindkrishna et al. (2009)			FSC			Implicit
Lee and Wu (2009)				VTT		Learning
Eren (2009)				VTT		Learning
Lodree and Geiger (2010)				VTT		Fatigue effect
Anzanello and Fogliatto (2010)				VTT	LR	Learning
Janiak and Rudek (2010)				VTT		Skills, learning
Pargar and Zandieh (2012)				VTT		Learning
Lee et al. (2012)				VTT		Learning
Nembhard and Bentefouet (2012)				VTT	S	Learning
Wang et al. (2013)				VTT		Skills
Zhang et al. (2013)				VTT		Learning
Costa et al. (2014)				VTT	S	Skills
Anzanello et al. (2014)	✓		TC	VTT		Learning, repetitive movements
Bautista et al. (2015)	✓			VTT		Learning, fatigue effect
Ji et al. (2015)				VTT		Learning
Ruiz-Torres et al. (2015)		MO	TC		P	Satisfaction
Amirian and Sahraeian (2015)				VTT		Learning
He (2016)				VTT		Learning
Zhu et al. (2017)				VTT		Fatigue effect
Pei et al. (2017)				VTT		Learning
Gong et al. (2018)				VTT	S	Skills
Przybylski (2018)				VTT		Learning
Li et al. (2018b)				VTT	LR	Learning
Lu et al. (2019)		MO				Noise
Petronijevic et al. (2019)						Learning, LFFRM
Sanchez-Herrera et al. (2019)				VTT	S	Fatigue effect
Jamili (2019)			TWC			Meal breaks
Sun et al. (2019)	✓		TWC			Meal breaks
Wang et al. (2019)				VTT		Learning
Sheikhalishahi et al. (2019)		MO				Human error
Ruiz-Torres et al. (2019)		MO-He			P	Satisfaction
Gong et al. (2020a)			CC		S	Skills
Savino et al. (2020)			TC			Posture
Kaya et al. (2020)	✓	MO				Noise, vibration, posture
Şenyiğit et al. (2020)				VTT		Learning, repetitive movements
Fu et al. (2020)			MO			Noise
Gong et al. (2020b)				VTT	S	Skills
Marichelvam et al. (2020)	✓			VTT	S, LR, PP	Skills, learning
Wang et al. (2020)				VTT		Fatigue effect, motivation
Zhang et al. (2021)				VTT	S	Skills, learning
Berti et al. (2021)				VTT	S, PP	Skills, EE, RA
Chen et al. (2021)				VTT		Learning
Hongyu and Xiuli (2021)		MO	CC	VTT	S	Skills, whole body
Tan et al. (2021)	✓	MO	CC, TC		S, PP	Skills, EE
Snauwaert and Vanhoucke (2021)			CC	VTT	S	Skills
Rinaldi et al. (2022)	✓		TC	VTT	S	Skills, handling, posture
Zhang et al. (2022)	✓		TC	VTT		Fatigue effect
Peng et al. (2022)		MO		VTT		Learning, noise
Lou et al. (2022)				VTT		Learning

focus on modeling *learning*, *fatigue*, or integrating *perceptual HFs*. An interested reader is referred to Biskup (2008) and Azzouz et al. (2018) for reviews dedicated to learning in machine scheduling.

Learning. The most common HAM found in the production scheduling literature is the organizational learning. The underlying idea is that the more similar tasks are repeated, the more *know-how* is acquired and the execution time decreases accordingly. One could argue that learning might not be determinant for production scheduling, given its short-term planning horizon. However, this effect has been widely accepted (Biskup, 2008). This topic has been extensively studied in the context of single machine scheduling (Biskup, 1999), parallel machine scheduling (Eren, 2009), or flow-shop scheduling (Wang and Xia, 2005). In this context, processing times and/or setup times are sequence-dependent (Amirian and Sahraeian, 2015), or dependent on the sum of processing times of similar tasks already processed (Cheng and Wang, 2000). It is also common to suppose that the processing times depend on both the position and the sum of processing times for similar tasks already processed (Wu and Lee, 2008; Wang et al., 2019).

Fatigue. With a modeling technique similar to that of the organizational learning, the processing times of the tasks are affected by the fatigue level of the operators. In the scope of production scheduling, fatigue is often not modeled at the individual level of the operator, but as a general factor. The modeling approach uses the fatigue effect and rate-modifying activities (see Prunet et al. (2024)). In short, the integration of the fatigue effect into a model means that productivity decreases as time passes. This is often modeled with a linear decay function (Lodree and Geiger, 2010). When scheduled, rate-modifying activities (i.e., rest breaks) enable the recovery of the operators and restore the productivity to its maximum level (see, e.g., Zhu et al. (2017)). Analytical results on the scheduling problem with fatigue are provided by Lodree and Geiger (2010). In some studies, the deteriorating effect is modeled by a more sophisticated function, where adaptation improves productivity at the beginning of the work shift, and fatigue reduces it at the end (see, e.g., Bautista et al. (2015)).

Perceptual factors. In some studies, a perceptual risk factor is integrated into models via the addition of a dedicated objective function, for example, related to noise pollution (Lu et al., 2019), or dust pollution (Fu et al., 2020). Kaya et al. (2020) consider noise pollution, alongside with vibration exposure and posture.

Other HFs. The machine productivity may be affected by other factors than learning or fatigue, for example, skills (Wang et al., 2013; Costa et al., 2014), boredom (Wang et al., 2020), or rest breaks (Berti et al., 2021). Finally, Sheikhalishahi et al. (2019) study a production scheduling problem with human errors, and incorporate them into an optimization model.

5.2. Assembly line balancing

Assembly Line Balancing (ALB) represents a particular class of scheduling problems, which are of great importance in manufacturing systems. The goal of these problems is to assign a set of tasks to a set of workstations and to schedule them over a finite time horizon. Each task is defined by a (constant) processing time, and subject to precedence relations with other tasks. It is asked to minimize a given function related to the balance of the workload among all stations or to minimize the number of stations for a given cycle time. HFs have been extensively addressed while studying ALB. This is not surprising considering its nature. In fact, the usual objective function of these problems is already to balance the *workload* among workstations. In the classical literature, the workload is often expressed as a function of operation processing times, but it is not far-fetched to think of workload as a physical workload for human operators. Furthermore, assembly line balancing problems are highly combinatorial, and their instances often admit a large number of optimal solutions. In this case, it is natural to discriminate between these solutions using a second objective function. Table 5 presents the works on this research stream, which focuses on *skills*, *WMSDs*, and *fatigue*. An interested reader is referred to Otto and Battaia (2017) for a review dedicated to the balancing of the physical ER via ALB, and to Peltokorpi et al. (2014) for an integrated analysis on the relevant HFs for assembly lines.

Skills. The skill level of an operator may be modeled through compatibility constraints (see Section 7.2), where some assignments task/workstation are infeasible because the task at hand requires a specific skill set, that the employee operating this workstation does not possess (Koltai and Tatay, 2013; Manavizadeh et al., 2013). Another option is to consider employee skills in terms of their impact on the task duration (see Section 7.3.1). In this case, all assignments task/workstation are feasible, but the processing time is affected by the skill level of the operator (Samouei and Ashayeri, 2019; Polat et al., 2016; Zhang and Gen, 2011). In some works, the processing time depends on the physical properties of the operators (e.g., age, gender) instead of actual skills. For instance, Efe et al. (2018) use this HAM, where the numerical values are derived from a statistical regression from an empirical dataset.

WMSD risk assessment. The workload to be balanced in ALB is often considered in terms of ER, which may be modeled via WMSD risk assessment methods. The repetitiveness of the assembly work is, for instance, linked to the apparition of WMSDs (Occhipinti, 1998). The OCRA index is the most common HAM for this kind of risk, and is used in several studies that aim at balancing the ER, either alone (Zhang et al., 2020; Akyol and Baykasoglu, 2019; Tiacci and Mimmi, 2018), or jointly with other methods (Bautista et al., 2016b). An awkward posture is another major risk factor in assembly work and is commonly considered in the ALB literature. Different HAMs may be used to model the postural load in ALB, for instance, the OWAS (Cheshmehgaz et al., 2012), the RULA (Bautista et al., 2016b) or the REBA index (Bortolini et al., 2017). Manual handling is also a risk factor considered in ALB (Bautista et al., 2016b).

Fatigue. Energy expenditure, as a fatigue HAM, is often use to compute the ER in the ALB literature. Battini et al. (2016a) propose a method called the *predetermined motion energy system* to easily compute the energy expenditure in assembly work. This HAM may then be integrated into optimization models in various ways. For instance, Battini et al. (2016a) and Bautista et al. (2016a) use it as an objective function to balance. In Finco et al. (2020b) and Ostermeier (2020), the energy expenditure of an operator affects the task duration at the corresponding workstation. This might also be done indirectly with the integration of rest allowance (Finco et al., 2021). A maximal value on the accumulated energy expenditure may also be used to prevent an important workload imbalance (Battini et al., 2017a).

Other HFs. Similar to other scheduling problems, a learning effect may occur when processing similar tasks at a given workstation, for instance in Otto and Otto (2014) and Ostermeier (2020). Another interesting research stream focuses on human–robot collaboration in assembly line balancing, where the high-ER tasks are primarily assigned to robots, or operators equipped with exoskeletons (Dalle Mura and Dini, 2022; Weckenborg et al., 2022).

5.3. Production planning and inventory management

This section covers the optimization problems related to the planning of manufacturing activities at the tactical level. Production planning and inventory management are crucial leverage of performance in any manufacturing system (Jans and Degraeve, 2008). Table 6 presents the retrieved corpus on the topic, which mostly focuses on *learning*, *human errors*, and *fatigue*. An interested reader is referred to Jaber et al. (2022) for a review on the integration of learning curves in lot sizing models.

Learning and forgetting. This topic is by far the most studied in production planning. In the context of batch manufacturing, there can be a long time between the production of two similar batches, and a significant forgetting effect can occur during this period. It is seen as an increased setup cost, and in that case, it is natural to study the impact of learning and forgetting effects on the optimal batch size. The topic has received some attention in the early literature (Muth and Spremann, 1983; Smunt, 1987). Different forgetting functions have been studied to model this HF (Teyarachakul et al., 2011). In more recent studies, it is common to use more sophisticated learning models. For example, the learning and forgetting processes affect both the productivity and the quality of the production in Jeang and Rahim (2019) and Jaber and Bonney (2003). Kazemi et al. (2016a) account for both motor and cognitive learning. In Jaber and Peltokorpi (2020), the number of employees working in a team affects the learning process. From the perspective of inventory management, Kazemi et al. (2015) and Kazemi et al. (2016b) study learning in the Economic Order Quantity (EOQ) with empirical studies. They realized semi-structured interviews with industry experts to gain practical insights to design a more accurate learning curve for the EOQ model they develop. Zanoni et al. (2012) study the vendor-managed inventory problem with learning and forgetting curves.

Table 5
Assembly line balancing references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Const.	Param.	HW	HAM
Doerr et al. (2000)			TC	VTT	S	Skills
Carnahan et al. (2001)		MO-He				Biomechanical
Chiang and Urban (2006)				VTT		Skills
Choi (2009)		MO-He				Implicit
Moon et al. (2009)		MO-Ho	CC		S	Skills
Corominas et al. (2010)				VTT	S	Skills
Otto and Scholl (2011)		MO-He	TC			Whole body
Zhang and Gen (2011)				VTT	S	Skills
Mutlu and Özgörmüş (2012)	✓		TC			Implicit
Cheshmehgaz et al. (2012)		MO				Posture
Xu et al. (2012)	✓		TC			Biomechanical
Koltai and Tatay (2013)			CC		S	Skills
Manavizadeh et al. (2013)			CC			Skills
Kara et al. (2014)		MO-Ho	TC, CC		S, PP	EE, cognitive, skills
Koltai et al. (2014)	✓		CC		S	Skills
Otto and Otto (2014)				VTT		Learning
Sotskov et al. (2015)				VTT		
Battini et al. (2016a)	✓	MO				EE
Bautista et al. (2016b)	✓	MO-He	TC			Handling, posture, repetitive movements
Polat et al. (2016)	✓		CC	VTT	S	Skills
Bautista et al. (2016a)	✓	SO				Handling, posture, repetitive movements
Ritt et al. (2016)				VTT	S	Skills
Battini et al. (2017a)	✓		TC			EE
Bortolini et al. (2017)	✓	MO		VTT		Fatigue effect, posture
Aroui et al. (2017)	✓	SO			S	Implicit
Sadeghi et al. (2018)	✓	MO-He	CC		S	Skills
Alghazi and Kurz (2018)	✓		TC			Implicit
Efe et al. (2018)	✓			VTT	S, PP	Skills
Tiacci and Mimmi (2018)		MO-He				Repetitive movements
Salehi et al. (2018)	✓		CC	VTT, VQ	S	Skills, human errors
Akyol and Baykasoglu (2019)		MO-He			S	Repetitive movements
Samouei and Ashayeri (2019)				VTT	S	Skills
Akyol and Baykasoğlu (2019)				VTT	S	Skills
Zhang et al. (2020)		MO		VTT	S	Repetitive movements
Finco et al. (2020b)				VTT		EE, RA
Ostermeier (2020)	✓			VTT		Learning, LFFRM
Finco et al. (2021)	✓			VTT	PP	EE, RA
Ozdemir et al. (2021)	✓	MO				Handling, posture, biomechanical
Mokhtarzadeh et al. (2021)		MO				Handling, posture, repetitive movements
Weckenborg et al. (2022)		MO	CC, TC			Skills, EE
Stecke and Mokhtarzadeh (2022)		MO-He	FBC			EE
Campana et al. (2022)		MO-Ho		VTT	S	Skills
Chutima and Khotsaenlee (2022)		MO	TC		PP	EE, equity
Katiraee et al. (2022)	✓		CC	VTT	S, PP	Skills, fatigue
Yılmaz (2022)		MO	CC		S	Skills, equity

Human errors. The topic of human errors is actually studied extensively in inventory and supply chain management, considering that it is not a prevalent topic in other decision problems. Gilotra et al. (2020) study a 2-echelon supply chain with considerations on carbon emissions and human errors. In Shin et al. (2018), the human errors are integrated as an additional cost in the objective function for a 2-echelon supply chain model. Khan et al. (2012) and Khan et al. (2014) study a vendor-buyer supply chain model with learning occurring on the production side, and human errors in the quality inspection for the customer side.

Fatigue. Employee fatigue is indirectly accounted for in production planning via the computation of a Rest Allowance (RA). The RA models the appropriate break duration to integrate in a given planning, in order to keep the ER at a reasonable level. The RA may be computed based on energy expenditure (Battini et al., 2017c; Condeixa et al., 2020) or based on the heat exposure of the employees (Korkulu and Bona, 2021). The RA can then be expressed as a monetary cost, based on wages paid during rest times, and integrated into the objective function. Fatigue may also be accounted for in terms of productivity: for example Givi et al. (2015b) propose a model where productivity and quality depend on the learning and forgetting effects as well as fatigue and recovery.

Other HFs. Another interesting work on the EOQ has been done by Ryan et al. (2011) in the framework of a collaboration between operation researchers and ergonomists. An ergonomic field study is conducted on a road maintenance site to identify the most relevant HFs, which are then integrated into an EOQ model. Sobhani et al. (2019) study the effect of the working environment on the vendor buyer inventory model, modeled as health-states via a Markov chain.

5.4. Design of systems

In this section, we present research works dealing with system design in a broad sense. Several classes of problems are represented, sharing the common point of using an optimization method to design the inherent aspects (e.g., layout, processes) of a manufacturing system. Table 7 presents the corresponding studies, which focus mostly on *fatigue*, *perceptual factors* and *skills and learning*.

Fatigue. Several studies use the energy expenditure to account for the ER when designing processes and layouts. Zhang et al. (2018) aim at balancing this ER and the handling distance, by optimizing the batch size and the sequencing of operations. Al-Zuheri et al. (2013, 2016) study an assembly process with workers walking from one station to another. In Diefenbach et al. (2020), the material handling is performed using an electric vehicle, and energy expenditure measures the ER of the loading and unloading operations.

Table 6
Production planning references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Const.	Param.	HW	HAM
Muth and Spremann (1983)						Learning
Smunt (1987)				VTT		Learning
Elmaghraby (1990)				VTT		Learning
Anderson and Parker (2002)				VTT		Learning
Jaber and Bonney (2003)				VTT, VQ		Learning, human errors
Ryan et al. (2011)	✓					Expert collaboration
Teyarachakul et al. (2011)				VTT		Learning
Khan et al. (2012)						Learning, human errors
Huang et al. (2012)				VTT	S	Learning
Zanoni et al. (2012)				VTT		Learning
Khan et al. (2014)						Learning, human errors
Givi et al. (2015b)		MO-Ho		VTT, VQ		Learning, LFFRM, human errors
Kazemi et al. (2015)				VTT		Learning
Andriolo et al. (2016)	✓	MO				Handling
Kazemi et al. (2016a)						Learning
Kazemi et al. (2016b)				VTT		Learning, expert collaboration
Khanna et al. (2017)				VQ		Human error
Battini et al. (2017c)		MO-Ho				EE, RA
Mokhtari and Hasani (2017)	✓	MO				Noise
Shin et al. (2018)		MO-Ho				Human error
Sobhani et al. (2019)	✓					Health state
Jeang and Rahim (2019)				VTT, VQ		Learning
Condeixa et al. (2020)		MO-Ho				EE, RA
Cui et al. (2020)		MO				Total cost function
Gilotra et al. (2020)						Human errors
Jaber and Peltokorpi (2020)				VTT		Learning
Tiwari et al. (2020)				VQ		Errors
Cai et al. (2020)	✓		TC	VTT		EE, RA, handling
Korkulu and Bona (2021)		MO-Ho				EE, RA, heat
Fu et al. (2022)				VTT		Learning
Asadkhani et al. (2022)				VQ		Learning, errors

Table 7
System design references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Const.	Param.	HW	HAM
Braun et al. (1996)	✓	MO				Biomechanical
Celano et al. (2004)						Psychosocial
Hopp et al. (2004)					S	Skills
Al-Zuheri et al. (2013)		MO			S, PP	EE, skills
Bukchin and Cohen (2013)				VTT	S	Skills, learning
Razavi et al. (2014)	✓	MO-Ho	TC			Noise
Al-Zuheri et al. (2016)	✓	MO	TC			EE
Botti et al. (2017)	✓		TC			Repetitive movements
Antonio Diego-Mas et al. (2017)	✓	MO-He				Biomechanical
Hu and Chen (2017)				VTT		Fatigue effect
Olivella and Nembhard (2017)		SO			S	Skills
Li et al. (2018a)	✓	MO				Cognitive, biomechanical
Zhang et al. (2018)	✓	MO				EE
Pistolesi and Lazzerini (2019)	✓	MO				Equity, visual
Glock et al. (2019c)	✓	MO-Ho	TC			LFFRM, biomechanical
Diefenbach et al. (2020)		SO				EE
Finco et al. (2020a)	✓	MO				Vibrations
Mateo et al. (2020)	✓		TC			Handling, anthropometric
Bortolini et al. (2021)		MO	TC			Repetitive movements
Fu et al. (2022)	✓	MO-Ho				Fatigue, RA
Liau and Ryu (2022)		MO			S	Skills, posture

Perceptual factors. Finco et al. (2020a) and Razavi et al. (2014) study the design of an assembly line system, with the objective of minimizing the vibration (resp. noise) exposure of the operators. In both problems, several types of equipment are available to mitigate the exposure, either at the source or at the individual level. The cost of the system is balanced with the worker exposure. Considering visual factors, Pistolesi and Lazzerini (2019) study a disassembly line, where several operators work simultaneously on the product to disassemble. The main issue is to organize the operations so that workers are able to work simultaneously on different faces of the product.

Skills and learning. In several cases, it is the overall organization of the workforce that is designed. For example, the cross-training strategy is designed to improve the workforce flexibility in the works of Hopp et al. (2004) and Olivella and Nembhard (2017). A work-sharing strategy is designed by Bukchin and Cohen (2013), where new employees share a part of their workload during their training time.

Other HFs. In Botti et al. (2017) and Hu and Chen (2017), the problem is to determine if each process should be manual or automated, depending on its characteristics. Li et al. (2018a) study a facility layout problem, which integrates the physical and mental ER of employees.

Table 8
Job rotation references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Const.	Param.	HW	HAM
Villeda and Dean (1990)			TC			Hazard exposure
Carnahan et al. (2000)		SO			PP	Handling
Tharmmaphornphilas and Norman (2004)	✓	SO			PP	Handling, noise
Bhadury and Radovilsky (2006)		MO				Motivation
Tharmmaphornphilas and Norman (2007)		SO			PP	Handling
Asawarungsaengkul and Nanthavanij (2008)			TC			Noise
Diego-Mas et al. (2009)		MO-He			PP, CPP	Biomechanical
Aryanezhad et al. (2009b)		MO-He	CC, TC		S, PP	Skills, noise
Nanthavanij et al. (2010)		SO	TC	VTT	S	Skills, hazard exposure
Azizi et al. (2010)		SO		VTT	S, CPP	Skills, motivation
Asensio-Cuesta et al. (2012b)	✓	MO-He				Repetitive movements
Asensio-Cuesta et al. (2012a)		MO-He	CC		S, PP, CPP	Skills, whole body
Otto and Scholl (2013)	✓	SO				Whole body
Huang and Pan (2014)	✓	SO				Anthropometric
Mossa et al. (2016)	✓		TC	VTT	S	Skills, repetitive movements
Yoon et al. (2016)	✓	SO	FSC			Posture
Wongwien and Nanthavanij (2017)			CC, TC	VTT	S	Skills, hazard exposure
Pata and Moura (2018)		SO	CC		PP, CPP	Implicit
Gebennini et al. (2018)	✓	MO	TC		PP	Handling, EE
Hochdörffer et al. (2018)	✓	MO-He	CC		S	Skills, whole body
Moussavi et al. (2019)	✓	SO	FSC			Biomechanical, equity
Sana et al. (2019)	✓	MO				Handling, repetitive movements, posture
Kovalev et al. (2019)		SO				Implicit
Botti et al. (2020)	✓	MO			PP, CPP	Repetitive movements
Mehdizadeh et al. (2020)		SO				Handling
Ayough et al. (2020)				VTT	S, LR, CPP	Learning, motivation
Rerkjirattikal and Olapiriyakul (2021)			CC, TC		S	Skills, noise
Battini et al. (2022)	✓	MO		VTT	S, PP, CPP	Skills, noise, vibrations, RA, motivation
Dalle Mura and Dini (2022)	✓	MO	CC, TC, FSC			Skills, EE

The mental strain is computed with the Subjective Workload Assessment Technique (SWAT) (Reid and Nygren, 1988), which evaluates job difficulty by giving a score between 1 and 3 to the three following different criteria: time load, psychological effort load, and psychological stress load.

6. Workforce-related problems

6.1. Workforce scheduling

6.1.1. Job rotation

Before being studied through the lens of OR researchers, job rotation first designates a managerial method that organizes worker shifts, such that an employee is assigned to different tasks/workstations throughout his/her shift. The purpose of this paradigm originates in HF/E with the objective of reducing occupational injuries and employee boredom. The frequent change of workstation indeed causes the physical exertion of the operator to be spread across different body regions, according to the proverb “a change is as good as a rest”. Assembly line balancing problems already aim at spreading the physical workload among workstations, yet it may not be able to eliminate completely workstations with high ER. In this case, job rotation ensures that several operators will share the burden of this workstation. Several field studies have highlighted the benefit of the implementation of job rotation: It reduces the exposure to awkward posture (Hinnen et al., 1992), cardiovascular load (Kuijer et al., 1999), or muscle fatigue (Hinnen et al., 1992). Furthermore, job rotation, as an organizational method, is also used by Human Resources to maintain a multi-skilled workforce, ensuring more flexibility to deal with variability (Otto and Battaia, 2017). Job rotation has been first formulated as a scheduling optimization problem by the pioneering work of Carnahan et al. (2000) that is, to the best of our knowledge, the first work that integrates methodologies from HF/E into OR and mathematical optimization. Table 8 presents the works on this stream, which study mostly *WMSD risk*, *boredom*, and *skills*. An interested reader is referred to Otto and Battaia (2017) for a review dedicated to the balancing of the physical ER via job rotation.

WMSD risk assessment. In job rotation scheduling, the objective is often to minimize the maximal ER accumulated by an operator over the planning horizon, computed via WMSD risk assessment methods. In these problems, it is often the case that economic-related quantities (e.g., size of the workforce, number of workstations) and operational ones (e.g., cycle time) have already been optimized and are used as input data. A common modeling method in job rotation is therefore to use a single objective function related to the maximum ER. It can be focused on the postural load, for example with the REBA index (Yoon et al., 2016), manual handling tasks with the JSI index (Tharmmaphornphilas and Norman, 2007), or whole body assessment methods like the EAWS (Otto and Scholl, 2013). It is also very frequent that several risk assessment methods are considered altogether in a single model with different objective functions. For example, Sana et al. (2019) use the NIOSH equation for lifting tasks, the OCRA index for repetitive tasks, and the RULA index for awkward postures. One of the main ideas behind job rotation is to ensure that one worker does not get assigned to a high ER task for a long period, thus avoiding increasing excessively the risk, especially on the same body region. A common modeling technique to avoid such situations is to use forbidden sequence constraints. In this case, the successive assignment of two high-workload tasks to the same operator is not allowed (Moussavi et al., 2019; Yoon et al., 2016).

Boredom. This factor, seen as a lack of motivation due to repetitive and monotonous work, may be accounted for with soft constraints, where one of the objectives is to minimize the maximal number of consecutive periods with the same task assigned to a given worker (Bhadury and Radovilsky, 2006). Another option to model boredom in job rotation scheduling consists in using a varying productivity rate for the employees, depending on how long they are affected to the same task (Azizi et al., 2010; Ayough et al., 2020; Battini et al., 2022).

Skills. As other classes of scheduling problems dealing with human operators, skill considerations are often present in the work on job rotation scheduling. This can be modeled with compatibility constraints, where certain workstations require specific skills that not all workers

Table 9
Work-rest scheduling references (see Section 3.2 for the table legend).

Reference	Case study	Modeling			HW	HAM
		Obj.	Const.	Param.		
Bechtold (1979)						Fatigue effect
Bechtold et al. (1984)				VTT		Fatigue effect
Thompson (1990)			TWC			Meal breaks
Bechtold (1991)				VTT	PP	Fatigue effect
Bechtold and Thompson (1993)				VTT	PP	Fatigue effect
Brusco and Jacobs (1993)			TWC			Meal breaks
Aykin (1996)			TWC			Meal breaks
Aykin (1998)			TWC			Meal breaks
Mehrotra et al. (2000)			TWC			Meal breaks
Brusco and Jacobs (2000)	✓		TWC			Meal breaks
Gärtner et al. (2001)			FBC			Work-stretch duration
Topaloglu and Ozkarahan (2003)			TWC			Meal breaks
Topaloglu and Ozkarahan (2004)		MO-He	TWC		P	Meal breaks, satisfaction
Janiak and Kovalyov (2006)			FSC			Work-stretch duration, hazard exposure
Bard and Wan (2006)	✓		TWC, FBC			Meal breaks
Thompson and Pullman (2007)						Work-stretch duration
Janiak and Kovalyov (2008)			FSC			Hazard exposure, work-stretch duration
Bard and Wan (2008)	✓		TWC			Meal breaks
Rekik et al. (2008)			TWC, FBC			Meal breaks, work-stretch duration
Sawik (2010)			FSC		S	Hazard exposure, work-stretch duration
Rekik et al. (2010)	✓		FBC			Work-stretch duration
Quimper and Rousseau (2010)			FBC			Work-stretch duration
Restrepo et al. (2012)	✓		FBC			Work-stretch duration
Chen et al. (2013)			TWC			Meal breaks
Widl and Musliu (2014)			FBC			Work-stretch duration
Jamshidi and Seyyed Esfahani (2014)		MO-Ho		VQ		Human errors, fatigue effects
Yi and Chan (2015)	✓				PP, CPP	Heat tolerance
Gérard et al. (2016)			TWC			Meal breaks
Restrepo et al. (2016)			TWC			Meal breaks
Yi and Wang (2017)			TC		PP	Heat tolerance
Bonutti et al. (2017)			TWC			Meal breaks
Sungur et al. (2017)		MO	TWC			Meal breaks
Zhao et al. (2019)		MO	TC	VTT		EE
Calzavara et al. (2019b)						EE, RA
Akkermans et al. (2019)			FBC			Work-stretch duration
Li et al. (2020)				VTT		Fatigue effect
Álvarez et al. (2020)	✓					Meal breaks
Fang et al. (2021)		MO-Ho	FBC	VTT	S	Skills, work-stretch duration

possess (Pata and Moura, 2018; Hochdörffer et al., 2018). Skills can also be modeled with different levels of proficiency, where the task duration will depend on the skill level of the employee it is assigned to Mossa et al. (2016) and Battini et al. (2022), or both the employee skill and boredom levels (Nanthavanij et al., 2010; Azizi et al., 2010).

Other HFs. On top of the classical WMSD risk assessment methods, perceptual risk factors are also considered to be mitigated by job rotation. These factors are, for example, the noise exposure of the operators (Tharmmaphornphilas and Norman, 2004; Aryanezhad et al., 2009b), or the vibration exposure (Battini et al., 2022). Ad hoc risk assessment methods based on biomechanical criteria are also commonly used (Moussavi et al., 2019).

6.1.2. Work-rest scheduling

In work-rest scheduling, the main decision is to determine when and how to place rest breaks in an employee's schedule. According to Lodree et al. (2009), the problem consists in "determining the number, placement, and duration of rest times during a work period". This problem is very relevant to industrial applications. Many empirical studies have shown the link between the fatigue level and: individual performances (Yung et al., 2020), diminished quality of work (Caruso, 2015), and increased safety problems (Lombardi et al., 2010). Unsurprisingly, the studies on work-rest scheduling, presented in Table 9, focus on break-related HAMs, i.e., *meal breaks*, *work-stretch duration*, *fatigue*, and the *comparison between break scheduling methods*. An interested reader is referred to Xu and Hall (2021) for a more detailed review of empirical work in work-rest scheduling.

Fatigue via meal breaks. One of the most basic approaches to integrating rest breaks into workforce scheduling is to consider meal breaks. This HAM is quite common, as it emerges from a very clear and straightforward operational constraint when establishing employees' schedules. In most jobs, a break is planned for the employees to get lunch. Hence, either the break is fixed in time, or a degree of flexibility is allowed for its scheduling. The easiest way to integrate flexibility to a given extent into scheduling models is to have a time window, in which the meal break should be scheduled. For these reasons, this approach has been used in the early literature on workforce scheduling (Thompson, 1990; Brusco and Jacobs, 2000), but also in more recent works on the topic (Chen et al., 2013; Brusco, 2008). The use of time windows is not restricted to meal breaks and can be used to add some flexibility when scheduling several breaks in a work shift (Mehrotra et al., 2000; Topaloglu and Ozkarahan, 2003; Bonutti et al., 2017).

Fatigue via work-stretch duration. Another common HAM for rest break scheduling is to use work-stretch duration modeled via forward–backward constraints (see Section 7.2). This approach is more sophisticated than using time windows, in the sense that it provides more possibilities. The schedules should abide by a set of "rules" about break placement. For example, a maximal work duration without a break, a minimal break time to be scheduled during a shift, a minimal duration for a break, a minimal duration between the shift beginning and the first break. Gärtner et al. (2001) is the first work, to our best knowledge, to propose this modeling framework, and other papers followed in this direction (Quimper and Rousseau, 2010; Restrepo et al., 2012; Rekik et al., 2010). An interested reader is referred to Widl and Musliu (2014) for a more theoretical analysis of the impact of work-stretch duration on scheduling models. In some cases, the rules determining

Table 10
Shift scheduling references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Const.	Param.	HW	HAM
Cai and Li (2000)			TC			Skills
Gans and Zhou (2002)		MO-Ho			S, LR	Skills, learning
Eitzen et al. (2004)	✓		TC		S	Skills, equity
Pan et al. (2010)		MO	CC, FSC		S, P	Skills, satisfaction
Knust and Schumacher (2011)			FBC			Satisfaction
Akbari et al. (2013)		SO	CC	VTT	S, P	Skills, fatigue effect, satisfaction
Lapegue et al. (2013)		MO	FBC			Equity
Nishi et al. (2014)		MO-He	FBC			Equity
Prot et al. (2015)	✓	MO	FBC			Equity
Dewi and Septiana (2015)	✓	MO-He				EE, cognitive
Cheng and Kuo (2016)		MO-He	FSC		S, P	Skills, satisfaction, equity
Shuib and Kamarudin (2019)	✓	SO	CC		S, P	Skills, satisfaction
Steenweg et al. (2020)		MO-He	CC		S	Skills, equity
Caballini and Paolucci (2020)	✓	MO-He	CC, TC, FSC		S	Skills, equity, handling, repetitive movements
Soriano et al. (2020)		MO-He			P	Satisfaction

the placement of breaks are modeled with sequence constraints. For example, Janiak and Kovalyov (2006), Janiak and Kovalyov (2008) and Sawik (2010) study the workforce scheduling problem in contaminated areas. In their modeling, inspired by the related work regulations, each work period must be followed by a rest period, whose length depends (exponentially) on the duration of the work period.

Fatigue via other HAMs. To reduce the fatigue level, the benefits of a rest break have also been studied. In the related works, the productivity of a given employee reduces over time, as his/her fatigue increases. Breaks are not necessarily included in a solution, but they enable full or partial recovery of the operator, resetting his/her productivity to its initial level. This approach is especially suited for applications focusing on the fatigue modeling aspect since the break placement and duration are linked to HF/E observational methods, instead of being an exogenous input data of the problem. This approach has been used in early works with the basic HAM developed by Bechtold (1979), then applied in early works on the topic (Bechtold et al., 1984; Bechtold, 1991), as well as more recent studies (Jamshidi and Seyyed Esfahani, 2014; Li et al., 2020).

Comparison between break scheduling methods. Finally, there are works that study different break placement methods, and analyze the impacts on the produced schedules. For example, Bechtold (1979) proposes several models of fatigue and rest periods in the context of workforce scheduling. Rekik et al. (2008) study the modeling of both time windows and work-stretch duration. Thompson and Pullman (2007) study the comparison between scheduling breaks in advance and doing so in real time.

Other HFs. The detailed modeling of the break scheduling rules may come from the factors related to the industrial application at hand, for example, heat exposure (Yi and Chan, 2015; Sadeghi-Dastaki and Afrazeh, 2018) or hazard exposure in contaminated areas (Janiak and Kovalyov, 2006, 2008; Sawik, 2010).

6.1.3. Shift scheduling

In the Shift Scheduling Problem (SSP), the main decision is to allocate the employees of a given workforce to different work shifts over a certain time horizon, usually weeks or months (Lodree et al., 2009). Each shift is characterized by a staff requirement, given by a number of employees to be scheduled in the shift, often with the associated skill set required to perform the operations that are planned. The objective is often to minimize the cost of the plan with penalties, that can be applied to favor aspects desired in the solution: equity between employees, workers' preferences, overtime (Lodree et al., 2009). The corresponding studies are presented in Table 10, and focus on *skills*, *working hours regulations* and *psychosocial factors*.

Skills. Considering the nature of the SSP and the scope of the present review, it is not surprising that skills are one of the main HFs considered in SSP (Akbari et al., 2013; Cai and Li, 2000; Eitzen et al., 2004). Skills are seen as different qualifications for the employees: the manufacturing system cannot run during a shift if certain jobs are absent from the production site, or are not in a sufficient number. This is well illustrated in industrial case studies. For example, Shuib and Kamarudin (2019) study an SSP in a power station, and the skills correspond to the different positions: chief charge engineer, senior/junior block operators, first/second patrolmen, control operators, etc.

Working hours regulations. The manufacturing systems modeled with an SSP are often running on a 24 h schedule, thus including the shift scheduling aspect. And as such, working hours regulations are of foremost importance in the industrial context. In optimization models, this can be modeled with forward/backward constraints (Nishi et al., 2014; Knust and Schumacher, 2011; Prot et al., 2015) or forbidden sequence constraints (Cheng and Kuo, 2016; Pan et al., 2010).

Psychosocial factors. Another important class of HFs considered in SSP relates to the psychosocial risk factors, the most popular being employee preferences and equity. In the 24 h shift work, some shifts are more draining than others (i.e., night shifts). If applicable, some work periods are less preferred than others (i.e., weekends, public holidays). For a manager, it is crucial to account for these aspects to ensure fairness between employees and keep the workforce satisfied. In the mathematical models, several works integrate the shift preferences of the employees. In this case, each employee gives its preferred shifts, either with scores or via a ranking system (Cheng and Kuo, 2016; Knust and Schumacher, 2011; Pan et al., 2010). In some models, the maximization of preferences is the sole objective (Akbari et al., 2013; Shuib and Kamarudin, 2019). The equity concerns in the SSP literature are not limited to preferences, other measures are used to balance the workload between employees, like the total working time, or the assigned shifts on public holidays (Prot et al., 2015; Lapegue et al., 2013; Cheng and Kuo, 2016).

Other HFs. Fatigue may be considered in SSP (Akbari et al., 2013; Dewi and Septiana, 2015). It is indeed particularly relevant for industrial cases running on a 24 h schedule.

6.2. Workforce management

6.2.1. Workforce planning

In this section, we focus on workforce planning problems. In this class of problems, the main decision is, for each period, to assign the employees to a set of tasks to be performed. The difference with

Table 11
Workforce planning references (see Section 3.2 for the table legend).

Reference	Case study	Modeling			HW	HAM
		Obj.	Const.	Param.		
Stewart et al. (1994)		SO	CC		S	Skills
Bordoloi and Matsuo (2001)	✓	MO-Ho			S	Skills
Wirojanagud et al. (2007)			TC		S, LR	Skills
Fowler et al. (2008)	✓		TC		S, LR	Skills
Aryanezhad et al. (2009a)		MO-Ho	CC		S	Skills
McDonald et al. (2009)	✓	MO-Ho	CC	VQ	S	Skills
Othman et al. (2012)		MO-He			S, PP, CPP	Skills, motivation
Kim et al. (2013)		MO-Ho				Total cost function
Attia et al. (2014)		MO-He	CC	VTT	S, LR	Skills, learning
Nembhard and Bentefouet (2014)				VTT	S, LR	Skills, learning
Hewitt et al. (2015)				VTT		Learning
Mehdizadeh et al. (2016)		MO-Ho	CC		S	Skills
Valeva et al. (2017)				VTT	LR	Learning
Wang et al. (2018)				VTT	S	Skills
Shahbazi et al. (2019)		MO-He		VTT	S	Skills, psychosocial
Cavagnini et al. (2020)				VTT		Learning
Ruf et al. (2022)		MO-Ho	CC		S	Skills
Jaillet et al. (2022)		MO-Ho			S	Skills
Rafiee et al. (2022)		MO-Ho	CC		S	Skills, learning
Doan et al. (2022)	✓	MO-He	CC		S, P	Skills, satisfaction, equity

the workforce scheduling problem lies in the planning horizon. The workforce planning process is located at the tactical level, therefore the planning horizon is rather long (e.g., weeks or months). This larger horizon means that tactical decisions (e.g., the size of the workforce) become available for the planner (De Bruecker et al., 2015). The hiring and firing processes are usually considered in these models, both coming at a monetary cost. In most problems, the skill pool of the workforce should remain sufficient to fulfill the requirement of each work period. Table 11 presents the works on the topic, with a focus on *skills*, and *skill development*. The interested reader is directed to De Bruecker et al. (2015) for a detailed literature review on workforce planning with skill considerations.

Skills. The most common HF in this class of problems is skills. They can be modeled with compatibility constraints, where only qualified employees can be assigned to certain tasks when individual assignments are modeled (McDonald et al., 2009). Another modeling approach is with resource constraints: In this case, employees are not modeled individually, the number of employees at a given skill level is considered as a resource, that needs to be above a certain requirement in each planning period (Fowler et al., 2008). Skills can also be modeled with varying task times (see Section 7.3.1), where the productivity of an employee improves with his/her skill level (Wang et al., 2018). More than productivity, the output quality level can vary with the skill of an employee (McDonald et al., 2009).

Skill development. With the tactical planning horizon, hiring and firing are not the only ways to adapt the skill set of the workforce. Some works explicitly consider human resource planning, where training can be scheduled to improve the skill level of an employee. In this case, the training comes at a monetary cost, either directly, or indirectly when an employee is unavailable due to training (Othman et al., 2012; Mehdizadeh et al., 2016) . Fowler et al. (2008) and Wirojanagud et al. (2007) are interested in the *General cognitive ability* of employees, affecting the required training time to pass from one skill level to another. The skill development does not necessarily come with training, but also via individual (i.e., autonomous) learning. More details on the difference between induced and autonomous learning are provided in Prunet et al. (2024), *Learning*. This is also considered in several works on workforce planning, where the repetition of tasks requiring a given skill increases the proficiency of an employee at this skill. Learning curves are used to model this autonomous learning (Nembhard and Bentefouet, 2014; Cavagnini et al., 2020).

6.2.2. Workforce assignment

In this section, we study the workforce assignment. This is not a unified class of problems, but we chose to regroup problems that assign a set of operators to a set of jobs or workstations. Generally speaking, this assignment decision is not the focus of these works *per se*, but one aspect of the decision-making process. Table 12 presents the works on the topic, with a focus on *skills* and *psychosocial factors*.

Skills. An important class of problems refers to the cellular manufacturing organization, where machines and processes are grouped into cells that produce a specific output. In this context, one step of the process is the assignment of workers to the set of cells. As usual, when dealing with problems related to workforce optimization, skills are a very common HF (Wu et al., 2018; Lian et al., 2018). Norman et al. (2002) focus their modeling of the skill aspect on both technical and human skills. Skill improvement can be considered through training (Norman et al., 2002), which is unusual with problems without a time horizon. In this example, a maximum training time is allowed to get the desired skill set in the workforce. For a person/job assignment problem, Sayin and Karabati (2007) use a 2-stage model to assign workers between several departments. The model is multi-period with the first stage consisting of assigning employees to departments by minimizing labor shortage, and the second stage aiming at maximizing skill development in the workforce.

Psychosocial factors. Several papers that study a general person/job assignment with a security concern (Zhang et al., 2019b), while accounting workers' sensitivity to risk (Lazzerini and Pistolesi, 2018), or accounting for cognitive aspects of the job and various human resources strategies (Fini et al., 2017). Brusco (2015) focuses on employees' preferences as a second objective function to determine the optimal person/job assignment.

Other HFs. Learning is also considered in this class of problems, for instance (Nembhard, 2001) studies a basic model of two jobs and workers with different learning rates. The author performs simulations under different experimental conditions to design a heuristic policy that maximizes total productivity. Equity is another common concern, where the aim is to balance the workload among employees (Lian et al., 2018; Wu et al., 2018).

7. Mathematical programming considerations

This section presents an analysis of the reviewed material from a mathematical programming perspective. The integration of HFs is

Table 12
Workforce assignment references (see Section 3.2 for the table legend).

Reference	Case study	Modeling Obj.	Const.	Param.	HW	HAM
Nembhard (2001)				VTT	LR	Learning
Norman et al. (2002)		MO-Ho	CC	VQ	S, CPP	Skills
Sayin and Karabati (2007)		MO			S	Skills, learning
Sueer and Tummaluri (2008)				VTT	S	Skills, learning
Egilmez et al. (2014)				VTT	S	Skills
Brusco (2015)		MO-He			S, P	Skills, satisfaction
Niakan et al. (2016)			CC, TC		S	Skills, noise
Ferjani et al. (2017)	✓	MO-He	CC		S	Skills, fatigue effect
Azadeh et al. (2017)		MO			CPP	Psychosocial
Fini et al. (2017)	✓	SO			S, PP, CPP	Cognitive, psychosocial
Lazzerini and Pistolesi (2018)	✓	MO			CPP, P	Satisfaction, expert collaboration
Wu et al. (2018)		MO-He		VTT	S	Skills
Lian et al. (2018)		MO		VTT	S	Skills, equity
Zhang et al. (2019b)	✓	MO-Ho	TC			Expert collaboration
Yilmaz (2020)		MO		VTT	S	Equity
Lee et al. (2022)	✓		CC			Hazard exposure
Daş et al. (2022)		MO-He			S, CPP	Skills, psychosocial

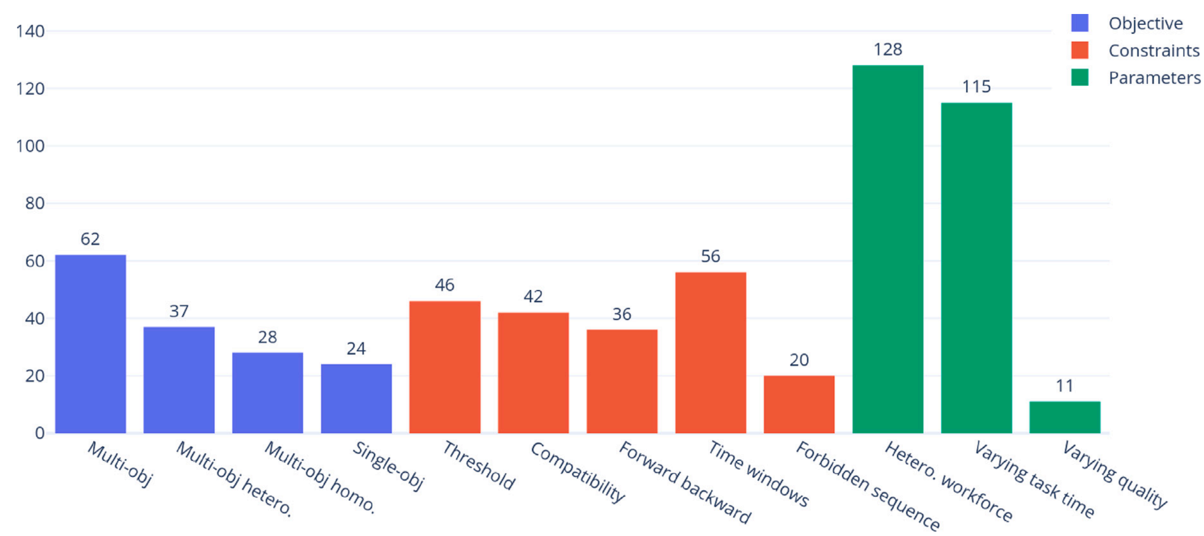

Fig. 2. Popularity of existing modeling techniques.

mainly performed through the objective function (see Section 7.1), constraints (see Section 7.2), or parameters (see Section 7.3). This section highlights the impact of HAMs on the structure and complexity of mathematical models and solution methods. Modeling approaches are linked to the most classical HAMs they are applied with. Examples are provided for illustration purposes, but mostly links are made toward topics discussed in Prunet et al. (2024). Fig. 2 shows the popularity of the modeling techniques found in the collected material. Note that the different techniques within the same category (e.g., constraints) are not mutually exclusive, as one paper may use several of those.

7.1. Objective function

In this section, we study models where HFs are integrated via an objective function. This is achieved either with a single human-aware objective function (see Section 7.1.1), or with the integration of a human-related objective function alongside other economic-related objectives (see Section 7.1.2).

7.1.1. Single objective optimization

A single ergonomic objective is very straightforward to handle from a mathematical point of view. However, considering only a HF-related objective is rarely sufficient while neglecting existing (economic) objectives. Since costs are not included in the objective, this modeling approach refers mainly to problems where the cost is fixed or bounded, and other quantities are balanced between employees/zones. This class of problems is mainly related to job rotation (Otto and Scholl, 2013), assembly line balancing (Bautista et al., 2016a), or storage assignment in warehousing (Otto et al., 2017). It can also be encountered in driver scheduling models (Otto et al., 2017). Mathematical models involving a single HF-related objective are used mainly in two cases: **(i)** for special-purpose models, or **(ii)** when dealing with equity concerns.

Special-purpose models. Special-purpose models heavily depend on the problem under study. One can cite (Stewart et al., 1994), where different training strategies lead to different objective functions related to the workforce (e.g., minimizing the training cost, maximizing the workforce flexibility). Sometimes the objective is to minimize the total ER of a plan without computing it for individual employees (Diefenbach et al., 2020).

Single equity objective. The main application found in the literature is to deal with equity between employees or lines in an assembly context. This is relevant for problems where the number of resources is already decided, and the goal is to balance these resources efficiently. It is in assembly line balancing or job rotation to find an assignment of operations that balances the workload *evenly* between the park of workstations. In the case of HAMs, this workload is, however, defined in terms of physical workload for the employees, or work-related injury risk. The HAMs used to estimate the ER to balance in a single optimization objective, include most observational methods (Bautista et al., 2016a), especially with lifting activities via the NIOSH-equation (Otto et al., 2017) or the JSI (Carnahan et al., 2000), but also with noise exposure (Tharmmaphornphilas and Norman, 2004).

Karsu and Morton (2015) provide a review of the different equity metrics found in the OR literature, i.e., the different functions that can be used to assess if a quantity is well balanced between a set of entities. In the works surveyed in the current review, where a single equity objective is used, the basic min–max balancing criterion is the most common. Here, a set of tasks $\mathcal{N}$, each with an associated ER p_i, $i \in \mathcal{N}$ has to be balanced between a set of employees $\mathcal{W}$ over a planning horizon $\mathcal{T}$. The assignment decision variable x_{iwt} is equal to 1 if task $i \in \mathcal{N}$ is assigned to employee $w \in \mathcal{W}$ during period $t \in \mathcal{T}$. Then the objective is to minimize the maximal accumulated risk over the planning horizon for the employees, as shown in the following equation:

$$\min \max_{w \in \mathcal{W}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} p_i x_{iwt}$$

For further analysis, the interested reader is directed to Karsu and Morton (2015).

7.1.2. Multi-objective optimization

Multi-criteria optimization is commonly used to include human well-being and safety in mathematical optimization because it allows taking into account both economic and ergonomic objectives at the same time. Despite the ease of modeling, the challenge of multi-criteria optimization resides in the handling of multiple (and often conflicting) objectives. We distinguish three possibilities to simultaneously handle multiple criteria:

- *Multiple objectives:* In this case all objective functions are fully considered in the model, and the aim is to compute, or estimate, the so-called Pareto-front. This approach is the most sound in terms of modeling, as no assumption is made on the preferences of the decision-maker.
- *Aggregation of heterogeneous objectives:* Another possibility is to work with objective functions expressed by heterogeneous quantities (like money and work-related ER), and to aggregate them nonetheless. The decision-maker then has to position the objective function of interest in relation to its relative importance. In this case, the considered objectives are aggregated with weights, which need to be tuned to look at the desired area of the Pareto front. This is, however, non-trivial and often requires a fair amount of work (Branke et al., 2008).
- *Aggregation of homogeneous objectives: In this case, objectives are expressed as* homogeneous quantities (like money) that are comparable. Therefore, multiple criteria can be added to the objective without requiring additional information.

Multiple objectives. Multi-objective optimization is a rather common way to account for HFs. It is used in various areas of logistics: assembly (Battini et al., 2016a), job rotation (Botti et al., 2020), warehousing (Larco et al., 2017), routing (Liu, 2016), scheduling (Lu et al., 2019), or lot sizing (Andriolo et al., 2016). In terms of HFs accounted for, the list is also diverse but mostly focused on ER assessment methods that are reduced or balanced. It includes energy expenditure, manual handling risk assessment methods, posture assessment, or general workload equity concerns.

Dealing with multiple criteria decision-making has an impact both in terms of complexity and choice of solution approaches (Branke et al., 2008). The multi-criteria aspect leads to several non-dominated optimal solutions with respect to the considered criteria, the so-called Pareto front. This approach is especially relevant for industrial applications, as the Pareto front provides a convenient visual representation for the decision-maker. To compute an estimate of this front or some of its particular points, two methods are mainly used: population-based metaheuristics, and non-interactive mathematical programming approaches.

Population-based metaheuristics are well-studied and have proven their efficiency in dealing with large-scale multi-criteria optimization problems (Branke et al., 2008). Several solutions are kept in memory at all times, with consideration for the population diversity, thus enabling the generation of a set of non-dominated solutions at the end. The most common metaheuristics found are variants of genetic algorithms (Sana et al., 2019; Al-Zuheri et al., 2016), as the NSGA-II algorithm (Rabbani et al., 2020; Azadeh et al., 2017). More seldom, other metaheuristics frameworks have been used, like the artificial bee colony (Li et al., 2018a), the particle swarm optimization (Cui et al., 2020), or the Grey Wolf optimization (Lu et al., 2019).

As far as mathematical programming is concerned, several common multi-criteria methods have been used in the context of this literature review. The most common one is the ϵ-constraint method, which enables the computation of several points of the Pareto front by optimizing over one objective, while the others are constrained by a given value (Bortolini et al., 2017; Finco et al., 2020a). A more basic version of this method is the optimization using lexicographic objectives, where one objective is first optimized and then constrained to its optimal value, then another objective is optimized, and so on. Compared to ϵ-constraint, this approach is more straightforward in its design and implementation but provides less information on the Pareto front (Lehuédé et al., 2020; Liu, 2016).

Aggregation of heterogeneous objectives. This modeling approach is fairly common since it is the most basic way to deal with economic and ergonomic objectives. In the retrieved corpus, it has been used in various areas of logistics and manufacturing. These include assembly line balancing (Otto and Scholl, 2011; Bautista et al., 2016b), job rotation (Diego-Mas et al., 2009), workforce scheduling (Yoon et al., 2016; Othman et al., 2012), and vehicle routing (Kim et al., 2006).

A naive method to construct an aggregate objective is, for a feasible solution $x \in X$, to associate with each objective function $g_i(x)$ a weight $0 < w_i < 1, i \in \{1, 2, \ldots, n\}$. These weights are usually normalized so that their sum is equal to one. The aggregate objective function is then the weighted sum of n objectives:

$$g(x) = \sum_{i=1}^{n} w_i g_i(x)$$

This is analytically and computationally rather easy to do. However, the fine-tuning of these weights is far from trivial to translate well the preferences of the decision maker into quantified trade-offs. Its ease of use has made the weighted sum method fairly popular in the present corpus. One can cite (Bhadury and Radovilsky, 2006; Bautista et al., 2016b) or Diego-Mas et al. (2009) with up to 45 criteria aggregated in a weighted sum. Goal programming is another widely used method to aggregate heterogeneous objectives. The idea is, for each objective function g_i to set a target value g_i^*, which corresponds to the desired value for the decision maker. Then the aggregate objective function is to minimize the weighted sum of the deviations from the target values. The advantage of goal programming over the weighted sum approach is that the target values have a concrete interpretation for the decision maker, and are therefore easier to compute. Furthermore, these targets provide natural values for the weights in the sum, by normalizing the deviation to the target value as a percentage. The objective function would then be:

$$g(x) = \sum_{i=1}^{n} w_i \frac{|g_i^* - g_i(x)|}{g_i^*}$$

An alternative exists, where the Chebyshev distance metric is used instead, i.e., the objective is to minimize the maximum (weighted) deviation from the target values. Goal programming has been used, for instance, in Choi (2009), Sungur et al. (2017) and Mokhtari and Hasani (2017).

Overall, a heterogeneous aggregation of several objectives is much easier to handle than true multi-objective optimization, both analytically and computationally. However, information is lost since a single solution is found instead of a set of non-dominated ones. This can make an actual implementation trickier to fine-tune to the decision maker's preferences.

Aggregation of homogeneous objectives. Another way to deal with multiple objectives is to convert them into homogeneous quantities. This way they are comparable, and the trade-off is easier to find. The big advantage of this kind of modeling is that the model has only one objective, thus being analytically and computationally easier, without requiring the decision maker to quantify his/her needs to fine-tune an implementation of the model. However, to be feasible, the considered objectives should be expressed in homogeneous quantities, which, depending on the context, can be rather difficult. Usually, the aggregated objective is expressed as a total cost since it is a rather common concern for companies to quantify the direct and indirect economic impacts of their decisions. Note that, to use this modeling, a HAM should be convertible to a monetary cost, which limits the applicability.

This modeling approach is interesting to use since it combines both accuracy in the decision-making process and ease of computation. However, the problem at hand should be compatible with such modeling, which is not always the case. It is used in different areas of logistics and manufacturing, such as lot sizing (Battini et al., 2017c), assembly line balancing (Kara et al., 2014), workforce scheduling (Jamshidi and Seyyed Esfahani, 2014) or warehousing (Battini et al., 2017b).

A common approach is based on fatigue with energy expenditure and rest allowance. The general idea is that when the fatigue level of an employee increases, the ER increases accordingly. Therefore, for each work period, one can compute a rest allowance corresponding to a break period enabling the recovery, which can easily be translated into a cost using the hourly wage of the employee since it corresponds to paid unproductive time (Battini et al., 2017c; Condeixa et al., 2020; Glock et al., 2019c). A high level of fatigue also leads to a rise in the error rate, which can easily be quantified as a cost and integrated into the objective function (Kuo et al., 2014).

Another common modeling refers to the WMSD risk. A high level of work-related injuries might impact indirectly several cost items of a company. Sobhani et al. (2017), Sobhani and Wahab (2017) and Sobhani et al. (2019) try to quantify this monetary impact. The objective function they use is expressed in terms of a monetary cost and includes several terms that correspond to different cost items, potentially impacted by poor working conditions: performance loss, injury leave costs, increased insurance costs, hiring and firing costs for replacement short-term employees or to compensate a high turnover rate, etc. Another interesting approach is to account for the cost of risk-mitigation measures when faced with a hazardous work environment. For example, Razavi et al. (2014) account for noise control in a manufacturing environment, and their objective function includes personal and machine equipment to keep the noise-related risks at an acceptable level.

Finally, when considering employees' skills, it is possible to link the skill level to productivity rate (Norman et al., 2002), error rate (McDonald et al., 2009) and, of course, wages (Moon et al., 2009). All these aspects impact the cost structure.

7.2. Constraints

Another widespread way to consider human-related factors in optimization models is across constraints. Several types of human-aware constraints can be identified within the collected material: *compatibility constraints*, *threshold constraints*, *forbidden sequence constraints*, and *work-stretch duration constraints*.

Compatibility constraints. Compatibility constraints are one of the most basic ways to integrate human considerations into mathematical models. They are mostly used when the aim is to assign a set $\mathcal{W}$ of human resources (often employees) to a set $\mathcal{N}$ of tasks in accordance with the skills of employees. Compatibility constraints are mostly used to model the skills and qualifications for workforce scheduling (Pan et al., 2010) or assembly line balancing (Manavizadeh et al., 2013), more seldom, for vehicle routing when drivers scheduling is integrated (Anoshkina and Meisel, 2020).

To better reflect practical considerations, additional modeling layers can be added to the problem. The idea behind this is always that a subset of assignments is forbidden. For example, each worker $w \in \mathcal{W}$ is associated with a set $\mathcal{N}(w)$ of tasks he/she is able to perform, or with the opposite view each task $i \in \mathcal{N}$ is associated with a set $\mathcal{W}(i)$ of workers that can perform it. When skills are explicitly accounted for, the problem definition contains a set $\mathcal{S}$ of skills that can represent either different competencies or qualifications, a single competence with different proficiency levels, or both at the same time. In this case, each employee w is associated with a set $\mathcal{S}(w)$ of skills he/she is able to perform, and each task i requires a set $\mathcal{S}(i)$ of competences to be operated (e.g., Pan et al. (2010)). Then an assignment is possible when the employee possesses the skills required for the task. Sometimes several employees can be assigned to a task, and the skill requirement applies to the group as a whole, and not to each individual. This is found in problems dealing with cell formation in manufacturing (Aryanezhad et al., 2009a), or technician routing problems (Mathlouthi et al., 2018), where the teams should have a broad skill set.

From a complexity perspective, these constraints do not significantly change the problem. With fewer feasible assignments, the problem becomes more constrained. It could therefore be more complicated to find feasible solutions, depending on the number of constraints applied to a specific instance. However, in the reviewed papers, the main challenge is the optimization of the problem since the skill resources are not scarce enough to make feasibility challenging. This modeling requires considering a heterogeneous workforce, slightly increasing the problem size depending on the granularity of the skill set (i.e., the number of skills considered). This modeling is, apart from early work, used mostly in addition to other human aspects that are computationally more challenging to consider in mathematical models.

Threshold constraints. Threshold constraints are mostly used when assigning or scheduling tasks. The idea is that each task is associated with an ER. Then there is a threshold value for accumulated ER for an employee over a shift. This modeling is mostly used when dealing with risk estimation methods, like WMSD risk assessment methods or energy expenditure. Sometimes it is also applied to environmental factors that are also linked to occupational risks, like noise or heat exposure. It is applied to various kinds of logistics and manufacturing problems related to assembly line balancing (Otto and Scholl, 2011), job rotation (Mossa et al., 2016), warehousing (Zhao et al., 2019), scheduling (Yi and Wang, 2017) or vehicle routing (Rattanamanee et al., 2015).

Threshold constraints are very classical in the OR literature, often called "capacity constraints". A set $\mathcal{N}$ of tasks has to be assigned to a set $\mathcal{W}$ of workers. Each task $i \in \mathcal{N}$ has a risk score $p_i > 0$. An assignment variable $x_{iw} \in \{0, 1\}$ is equal to 1, if task $i \in \mathcal{N}$ is assigned to worker $w \in \mathcal{W}$ during the shift. A threshold value p_{max} is given and should not be violated by the accumulated ER of tasks assigned to each employee, ensuring the risk remains at an acceptable level. Then, the threshold constraint is of the form:

$$\sum_{i \in \mathcal{N}} p_i x_{iw} \leq p_{max} \qquad \forall w \in \mathcal{W}. \tag{1}$$

The modeling of the assignment task/employee can be more sophisticated, especially when considering the scheduling of the tasks, where time is accounted for. Usually, in this family of constraints, the sequencing of tasks does not matter. Often the risk level of a task is weighted by the time spent performing this task, according to a given ER assessment method. Nevertheless, this family of constraints is ultimately equivalent to the basic form of Inequalities (1). The value of the threshold p_{max} is often derived from the risk assessment method and is set to an acceptable risk level for the shift. The risk assessment method can be: the OCRA index (Mossa et al., 2016), the NIOSH-equation (Mateo et al., 2020), the energy expenditure (Zhao et al., 2019), or the DND (Razavi et al., 2014). Sometimes the threshold value is set with respect to legal constraints about employees' exposure, e.g., related to toxic substance exposure (Villeda and Dean, 1990). In Ruiz-Torres et al. (2015), the opposite constraint is used, where each employee satisfaction level should be above a given threshold.

Forbidden sequence constraints. Forbidden sequence constraints are used to avoid some successions of tasks/shifts when designing a schedule. Indeed, when performing a physical task of high intensity, the ER increases with the duration of the task. In observational risk estimation methods, the exertion duration is often a key parameter. A forbidden sequence constraint ensures a maximum number (often one) of successive strenuous tasks scheduled for a given operator. The threshold constraints are a suitable method to limit the risk exposure of an employee on his/her shift. However, they miss a key component of the risk estimation, namely, the duration of the uninterrupted exertion. Forbidden sequence constraints are a way to bring more refinement and accuracy to models that already have mechanisms to limit/balance the ER over a shift (see e.g., Moussavi et al. (2019)). Naturally, forbidden sequence constraints are mostly found in job rotation models (Moussavi et al., 2019; Yoon et al., 2016), or work-rest scheduling problems, since they account for the sequence of assigned tasks to a workstation or an employee (Gärtner et al., 2001; Aravindkrishna et al., 2009).

In terms of complexity, these constraints are rather straightforward to handle from a modeling point of view. However, the problem becomes significantly more constrained. Moreover, the insertion of these constraints in an existing model might lead to infeasibility, and overall feasibility becomes more complicated to ensure. One should note that the reduction of successive high workloads is also commonly found as an objective function instead of a constraint (Asensio-Cuesta et al., 2012b; Botti et al., 2020). Modeling this aspect as an objective addresses the aforementioned drawbacks of the forbidden sequence constraints, however, other difficulties might arise with the handling of several objectives (see Section 7.1).

Time window constraints. The time window constraint is a widely used modeling technique in OR (see Fig. 2). It applies mostly when scheduling a set of activities, that need to be performed in a given time frame. In these problems, decisions have to be made related to the start time of a given set $\mathcal{N}$ of operations. For a given activity $i \in \mathcal{N}$, a time window constraint ensures that the activity i starts during a given time window $[a_i, b_i]$. With t_i the decision variable defining the start time of the activity, the mathematical constraint is then $a_i \leq t_i \leq b_i$.

In the scope of this review, the activities concerned with time window constraints are work breaks. There are indeed several ways to model the integration of breaks in a workforce schedule, the most basic one being through time windows. It corresponds to mostly early work on the topic, where a meal break has to be scheduled in the work shift with a flexible start time (Thompson, 1990). However, the meal break should happen roughly at mealtime, thus the time window. In the retrieved corpus, this modeling is mostly found in workforce scheduling problems (Brusco, 2008; Brusco and Jacobs, 2000), but also within the routing literature when driver meal breaks need to be scheduled (Kim et al., 2006; Coelho et al., 2016).

In terms of complexity, time window constraints are often easy to integrate. This modeling adds a number of activities to schedule (the breaks) on top of the productive tasks, which constraint slightly the problem. Although the consideration of time window constraints was challenging in the early literature on the topic (Solomon and Desrosiers, 1988), they are nowadays common and well-studied features in various classes of problems. In most applications, they do not provide a significant algorithmic challenge compared to the other constraints in the model.

Forward-backward constraints. Forward-backward constraints are commonly used when dealing with break scheduling. With this approach, a set of rules is defined to ensure that the quantity, duration, and/or placement of breaks comply with either work regulations or company policies. The objective is to give the mathematical models more flexibility than using time windows while prohibiting schedules that are of poor interest in practice. For example, scheduling a break just after the shift starts, or scheduling all the breaks one after another. In practice, rest breaks should be spread over the work shift to enable recovery. The rules defining the forward–backward constraints vary from one paper to another, more details can be found in Prunet et al. (2024), *Regulatory breaks and Work-stretch durations*, but some examples would be: "The first break should be scheduled at least 2 h after the shift starts", "A shift should contain one lunch break of a minimum duration of 1h" or "The work duration between two consecutive breaks must be at least 2 h, and at most 4h".

A more theoretical and general description of forward–backward constraints can be found in Widl and Musliu (2014) and Rekik et al. (2008). There are two main areas of application to forward–backward constraints: shift scheduling and vehicle routing. In vehicle routing, these rules are usually aligned with official regulations. Several countries have legislated on truck drivers' working times. The rules depend on the country, but follow the same framework (Goel, 2009; Prescott-Gagnon et al., 2010; Rancourt et al., 2013). Work-rest scheduling is the other main application area of forward–backward constraints. There is no regulation to comply with in this case, however, the flexibility allowed by this modeling is still worth considering (Gärtner et al., 2001; Restrepo et al., 2012; Quimper and Rousseau, 2010).

The flexibility gained from this modeling approach often leads to better quality solutions compared to time window constraints (Rekik et al., 2008, 2010). However, this flexibility comes at a cost in terms of complexity. One common technique to deal with this complexity is to consider break placement implicitly. This can be done directly in the formulation (Rekik et al., 2010), or these aspects can be convexified in the subproblem within a decomposition framework (Prescott-Gagnon et al., 2010; Ceselli et al., 2009).

7.3. Parameters

The HFs might be integrated directly in the parameters of the problem, either with *varying task time*, *varying quality*, or a *heterogeneous workforce*. The impact on optimization models varies depending on which aspect is considered and how it is integrated. Nevertheless, one can assume that considering heterogeneous characteristics will often increase the computational burden that follows by the need to consider extra dimensions in the mathematical models. These extra dimensions may be the time needed to capture the change of a parameter over the shift. It can also be the explicit consideration of employees to take into account their different skills. Finally, the model can be stochastic in nature.

7.3.1. Varying task time

Varying task time is one of the main ways to model HFs in optimization models (see Fig. 2). It is indeed a very flexible tool, which can be adapted to a wide range of HFs, and fits well in the OR frameworks. The idea is rather simple: instead of being a fixed parameter, the processing time of a task performed by a human operator varies. This variation can be purely stochastic to model the intrinsic variability of the performance of a human operator (Chiang and Urban, 2006; Egilmez et al., 2014; Sotskov et al., 2015). However, most of the time, processing times are deterministic and depend on the characteristics of the operator (e.g., skill, fatigue level). In terms of application fields, this modeling is mostly used in operational problems, where the granularity of the modeling allows us to consider individual execution times. Scheduling problems are a natural application, for example, production scheduling (Lee and Wu, 2009; Gong et al., 2020b), workforce scheduling (Yilmaz, 2020), or assembly lines (Ostermeier, 2020). Other applications are found in logistics, such as warehousing (Matusiak et al., 2017), or vehicle routing (Yan et al., 2019). Furthermore, this topic has also been studied from a more theoretical perspective with complexity studies (Janiak and Rudek, 2010; Lee and Wu, 2009; Wu and Lee, 2008).

Several factors are found to affect the processing time of tasks, as the workforce skills (Akyol and Baykasoğlu, 2019; Azizi et al., 2010), or the position of the task in the shift schedule (Biskup, 1999; Otto and Otto, 2014). The task time depending on its position in a shift is a very common modeling approach for problems related to employee learning since the repetition of a similar task improves the efficiency of the operator. However, it is also used to model a fatigue effect, where the productivity of an operator decreases as fatigue increases toward the end of a work shift (Sanchez-Herrera et al., 2019; Wang et al., 2020). Another very similar modeling technique is to adjust the processing time of a task depending on the sum of the processing times of tasks scheduled before. This is a very common modeling approach to the learning process (Zhang and Gen, 2011; Wang et al., 2019). It is also used when dealing with fatigue, where the productivity of an employee decreases according to a given function that depends on the time passed since the last rest break. In some papers, learning and fatigue effects are considered together, with their opposite effects on processing time (Givi et al., 2015b; Ostermeier, 2020).

The impact on optimization models varies depending on which aspect is considered, and how it is integrated. Nevertheless, one can assume that considering varying task times will often increase the computational burden of the models. It is however interesting that for scheduling models the problems seem to stay polynomial in several cases (Wu and Lee, 2008; Lee and Wu, 2009).

7.3.2. Varying quality

Some researchers consider that the quality level of the production is not a fixed exogenous parameter, but depends on the characteristics of the employee operating the given task. Several factors can be used to measure the quality level of production. The most common one is the skill level of the employee performing the task (De Bruecker et al., 2015). A varying quality level is mainly used when dealing with workforce planning when it depends on the skill level (Norman et al., 2002; McDonald et al., 2009). Learning, as the determining factor of the quality level, has also been used in the literature. One can especially cite (Givi et al., 2015b) and Givi et al. (2015a), who extend the learning forgetting fatigue recovery model to account for a quality improvement in the learning process. Another possibility is to model the error rate through a probabilistic framework. Khan et al. (2012) and Khan et al. (2014) study the human error taxonomy and classification with associated probabilities. In some other applications, errors are modeled using random variables with known density functions (Shin et al., 2018; Gilotra et al., 2020).

Employee fatigue is another major source of errors, and several empirical studies show a clear link between human fatigue and production quality (Yung et al., 2020). This source of errors is, for instance, a common consideration in warehousing studies focusing on order picking (Zhao et al., 2019; Grosse et al., 2017b).

7.3.3. Heterogeneous workforce

Other models worth mentioning are those considering a heterogeneous workforce. Historically, the homogeneity of the workforce is a common assumption in OR models. It is indeed generally very convenient from a mathematical point of view, and the hypothesis is valid for a number of applications. However, in some cases, a finer granularity in the modeling of the workforce is necessary to consider certain effects. This modeling is not attached to a particular HAM and is most of the time used within another modeling approach (e.g., objective function, or constraints). An interested reader is referred to Katiraee et al. (2021) for a dedicated review on the topic.

A heterogeneous workforce is naturally encountered when dealing with skills, otherwise all employees would have the same skill set. This case is denoted *S* in the result tables. The underlying idea of integrating skills in an optimization model can be twofold: **(i)** Employees as a heterogeneous set of resources. In this case, the skills represent different jobs or qualifications, enforced via *compatibility constraints* (Calzavara et al., 2019a; Hochdörffer et al., 2018; Joo and Kim, 2013), or **(ii)** Employees as a single set of resources, yet with different throughput/cost. In this case, the skills represent the proficiency of the employee on a set of tasks, enforced with *varying task times*, or *varying quality* (Hong, 2018; Khan et al., 2012; Matusiak et al., 2017). Note that neither case is exclusive to each other.

Related to skills, learning rates can also vary between employees. This case is denoted *LR* in the result tables. When working with learning curves, it is reasonable to suppose there is some discrepancy between employees in terms of learning rates. This modeling is mostly used in studies that focus on modeling with more accuracy the performances and their variations in a workforce. It has mainly seen use in workforce-focused problems, like workforce planning (Fowler et al., 2008; Attia et al., 2014), but also warehousing (Grosse and Glock, 2015; Grosse et al., 2013), machine scheduling (Marichelvam et al., 2020), shift scheduling (Gans and Zhou, 2002), and job rotation (Ayough et al., 2020).

The heterogeneity of the workforce can also be based on other intrinsic properties of its components. In the result tables, this is referred to as *PP* for Physical Properties, and *CPP* for Cognitive and Psychosocial Properties. These parameters are mostly risk factors for developing WMSD and are accounted for when computing the estimation of the ER of a work situation. It is indeed known that individuals have different chances of developing occupational diseases when facing a given work situation (Bridger, 2018). This can depend, for example, on the age of the person (Yi and Wang, 2017), his/her lifting capabilities (Carnahan et al., 2000), the physical fatigue he/she can safely sustain (Rattanamanee et al., 2015) or even its smoking and drinking habits (Yi and Chan, 2015). However, most of the time the individual physical parameters can be seen as *skills* in the sense that they affect the processing times of tasks or learning characteristics. Concerning psychosocial characteristics, they can be used to create teams with compatible decision-making styles (Azadeh et al., 2017), to account for the carefulness of the employees in a context of hazardous work environment (Lazzerini and Pistolesi, 2018), or to consider the motivation and personality of individuals when assigning tasks (Othman et al., 2012).

The last parameter that can differ between employees is their individual work preferences, noted *P* in the result tables. This parameter is used when accounting for the satisfaction of the workforce, either as an objective function, or threshold constraints that enforce a minimal satisfaction level for each employee, in a search for equity (Ruiz-Torres et al., 2015, 2019; Akbari et al., 2013).

Modeling the workforce as heterogeneous might have a substantial impact on decision models. The most obvious one is that a parameter that was constant over the workforce now depends on the concerned individual. This means that the decision variables should be able to model the individual assignment/schedule of the employees. Note that this is most of the time already the case in the problems studied in this review, especially the workforce-related ones. This individual-dependent parameter can add some complexity to an existing model. However, it also breaks symmetries, which is often beneficial for the performance of solution approaches, especially when using mathematical programming-based methods (Margot, 2010).

8. Discussion and future research

The analysis of the collected material brings out a large variety of works on the topic of integrating HFs into decision models for logistics and manufacturing systems, both in terms of studied problems, modeling approaches, and considered HFs. However, in light of the insights gained from the cross-analysis performed in both parts of the review, some gaps still remain to be filled. In this section, we discuss the collected material and propose some research directions that appear promising for future works, namely the relationship between HFs and fields of application (Section 8.1), the under-represented decision problems (Section 8.2), and the modeling of modern industrial practices (Section 8.3). The reader interested in a study of the different modeling of a HF depending on the field of application is referred to the second part of this work (Prunet et al., 2024).

8.1. Discussion on the relationship between HFs and fields of application

Upon reviewing the collected material, it becomes evident that the preponderance of the studied HFs varies between logistics and manufacturing problems, as illustrated by Table 13 that highlights the relationships between decision problems and HFs. This observation can be mainly explained by two factors: either the combination is irrelevant to the study, or the topic has not been thoroughly exploited and presents a direction for future research.

Learning. While extensively studied in some applications (e.g., production planning and scheduling), learning is seldom integrated into other scheduling problems where it could be relevant. This is especially true for applications where employees perform different kind of tasks, and thus where learning and forgetting occur when the task assignment changes: assembly line balancing, job rotation, and work-rest scheduling. Accounting for learning in job rotation would allow to discriminate equivalent solutions in terms of painfulness (Ayough et al., 2020). Vehicle routing is another field where learning is largely absent, despite the relevance of the learning process of drivers. Few works in the literature account for driver learning (Battini et al., 2015; Ulmer et al., 2020; Bakker et al., 2021), yet driver familiar with the roads may anticipate traffic jams and use alternative routes, thereby reducing the travel time. The learning process also applies to the customer locations, where service times might be reduced when drivers become more familiar with the locations.

Fatigue. The topic is studied in almost all fields, often using different HAMs. Although several fields extensively study the fatigue phenomenon via different HAMs, the explicit consideration of *when* to schedule rest breaks is mainly prevalent in vehicle routing and work-rest scheduling, despite being a powerful tool to reduce fatigue. The use of work-stretch duration to explicitly schedule rest breaks is a promising research direction in areas like warehousing or job rotation. The routing literature is another research direction for fatigue considerations. Although this interaction is profusely studied, it is almost exclusively using hours of service regulations. The work of Fu et al. (2022) is the only exception, as it accounts for biological indicators to schedule drivers' breaks. Further studies on vehicle routing with alternative fatigue HAMs would enrich the literature on the topic. Finally, energy expenditure is only used twice in the job rotation corpus, despite providing a convenient indicator to estimate the ER to balance between employees.

WMSD risk assessment methods. A large class of problems integrates WMSD risk. Shift scheduling and workforce planning are the two notable exceptions, which is unsurprising as they consider longer time horizons. Despite being challenging to model, the balancing of the WMSD ER is, however, still relevant as the risk builds over time, and more works should pursue this direction (Caballini and Paolucci, 2020).

Cognitive, psychosocial and perceptual factors. These factors are overall understudied, despite being relevant for a large class of problems. Noise and vibration exposure, for example, would be worth investigating in all the applications involving heavy machinery, such as assembly line balancing, production scheduling and planning, work-rest scheduling, or job rotation. Although employee satisfaction is rarely considered in the workforce planning literature, it plays an important role in the rate of turnover that is often considered in this class of problems (Doan et al., 2022). Finally, boredom would be an interesting research direction for the literature on warehousing and assembly line balancing, given the highly repetitive nature of the corresponding jobs.

8.2. Under-represented decision problems

Cases where the study is not relevant. Some HFs may not be relevant to be studied within specific applications. The first example that comes to mind is perceptual and environmental factors: it does not make sense to study heat or noise exposure when they do not pose a risk factor in a particular application, similarly visual considerations are only relevant in some applications (e.g., when an operator spends an important portion of the time visually searching for items to pick). Other examples include the HFs that are relevant for the application at hand, but where the optimization problem cannot modify the associated risk. This is for instance the case for posture-related risk in the routing literature: while the prolonged sitting position may be harmful to drivers, their exposure level is only marginally affected by the routing plan. Finally, there are some cases where the HF is simply not applicable for some classes of problems. The most straightforward example is when studying problems that do not integrate time aspects, such as layout design or inventory management, where the scheduling of rest breaks is not applicable. To cite another example, skills constitute the most studied topic, but are not relevant when applied to production planning, as individual employees are not modeled. Hours of service regulations are almost exclusively studied in the routing literature, because of the complex legislation enforcing them (Prunet et al., 2024). When applied to other problems, similar fatigue considerations are modeled via work-stretch duration. Finally, fatigue can be considered as a "short-term" effect, and thus it is understandably under-studied in problems with long time horizons that do not decompose a shift (shift scheduling, workforce planning and assignment). The interested reader is referred to Prunet et al. (2024) for additional discussions on the cross-dependency between HF and application.

Layout design problems. The design of workstation layout is one of the main study directions in HF/E and is an important lever of ergonomic improvement in a work situation (Bridger, 2018). However, the OR literature on the topic is scarce. More than designing workstations *per se*, for instance, studied in Antonio Diego-Mas et al. (2017), optimization algorithms enable a cost–benefit analysis of different solutions. For example, Razavi et al. (2014) and Finco et al. (2020a) study the economic and ergonomic impacts of using protective equipment for, respectively, noise and vibration exposure. Within warehousing logistics, Glock et al. (2019a) study the possibility of rotating pallets to enable easier access to the stored items, and Calzavara et al. (2017) or (Calzavara et al., 2019a) study the design of the storage racks and assess the economic and ergonomic impacts of different technological solutions. Overall, more works should study the impact of different technological solutions by the means of optimization problems.

Maritime logistics problems. Despite being an important class of problems within logistics (Christiansen et al., 2007), the integration of HFs remains lacking with these problems. Actually, a single work has been retrieved by our search methodology (Caballini and Paolucci, 2020). Future research should determine which HFs are important for this research stream, and integrate them in models. For instance, fatigue and skills may be relevant considerations for ships sailing around the clock.

Table 13
Cross-analysis of the human factors studied by field of application.

	Skills	Learning	Energy expenditure	Rest allowance	Fatigue effect	Learn forget fatigue recovery	Meal breaks	Hours of service regulations	Work-stretch duration	Whole body	Manual handling	Working posture	Repetitive movements	Motivation and boredom	Satisfaction	Psychosocial factors	Cognitive factors	Noise exposure	Visual considerations	Heat exposure	Vibration exposure
Warehousing	4	3	6	2	1						3	4							1		
Vehicle routing	4	3	2		1		8	23			1				1	3			1		
Production scheduling	14	31	2	1	6	1	2			1	1	3	2	2	2			4	1		1
Assembly line balancing	20	2	8	2	1	1				1	4	6	6	1							
Production planning		18	4	4		1					2							1		1	
Design of systems	5	1	4		1	1					1	1	2			1	1	1	1		1
Job rotation	10	1	2	1						3	6	2	4	4				5			1
Work-rest scheduling	1		2	1	6		16	1	12						1					2	
Shift scheduling	9	1	1		1						1		1		5		1				
Workforce planning	16	6												1	1	1					
Workforce assignment	10	3			1										2	3	1	1			
Total	93	69	31	11	18	4	26	24	12	5	19	16	15	8	12	8	3	12	4	3	3

Economic quantification of the indirect cost of poor ergonomics. Some studies presented in this review integrate HFs with their models by computing the cost of poor working conditions, due to e.g., injuries or turnover, and account for this cost in the objective function (see Prunet et al. (2024), *Total cost function*). For example, in the model proposed by Sobhani et al. (2015, 2017) and Sobhani and Wahab (2017), a Markov chain is used to determine the steady state of the number of injured employees and consequent sick leaves. This value is then used to compute the indirect costs of such leaves. It accounts for performance loss, injury leave costs, increased insurance costs, hiring, training, and firing costs for replacing the injured employees with short-term workers, and, finally, to compensate for the higher turnover rate linked to the degraded working conditions. Further research in this direction could be beneficial for the community, helping to present more comprehensive models for decision makers and be the basis of cost/benefit analysis for the consideration of HFs in the optimization of logistics and manufacturing systems.

Heterogeneous modeling of employees. Human characteristics are intrinsically subjected to personal variability. This is the case when considering human performance estimation, where each individual will have different levels of productivity, depending on the task at hand, his/her age, experience, etc. Moreover, a task might present a high level of risk for an individual, and an acceptable risk for someone else. This could be affected by several characteristics of the individual, e.g., age, height, and health conditions. However, in the literature, the norm is mostly to consider the workforce as a homogeneous pool of employees. This assumption of homogeneity makes sense when not considering HFs, yet it leads to a net loss of accuracy in the modeling when human characteristics are involved. In HF/E, anthropometry (i.e., the study and measurement of the human body) is an important field of study (Pheasant and Haslegrave, 2018), as it provides help to design work situations that would be safe and adapted for a large part of the working population (e.g., suited for 95% of the concerned population).

Integration of human-related variability. There is an intrinsic variability in human performances. In this review, several works focused on the modeling of human aspects for performance evaluation, sometimes with sophisticated models. However, few works integrate stochasticity into their modeling, despite it being an appropriate tool for the modeling of the variability. Furthermore, stochastic optimization is a well-studied area of OR, which could lead to interesting developments, by using methods historically originating from OR to deal with HFs in models.

8.3. Modeling of modern industrial practices

The rise of Industry 4.0, followed by the beginning of Industry 5.0, has led to the development of new practices in the logistics and manufacturing industries. Some of these innovations change the way the operators interact with their work environment. Future research should aim at accounting for these new practices, to bridge the gap between theory and practice.

Human–robot collaborative systems. This kind of organization is becoming more and more present in industrial systems. Indeed, human operators are more suited to tasks that require dexterity or decision-making, whereas robots are adapted to tasks with poor ergonomic conditions (e.g., repetitive tasks, heavy material handling, and use of hazardous tools). Human–robot collaborative systems have been studied in the collected material (Hu and Chen, 2017; Zhang et al., 2022; Stecke and Mokhtarzadeh, 2022; Lee et al., 2022), but the topic is still under-represented in the literature considering its importance in manufacturing (Jahanmahin et al., 2022b) or warehousing (Pasparakis et al., 2023). Future research directions follow the question raised by human–robot collaboration: Which tasks should be performed by humans/robots? How to organize the process such that operators remain safe around robots? How to schedule such a system.

Augmented workforce. Related to the development of human–robot collaboration, the augmented workforce is becoming a reality for demanding tasks where automation is ineffective (Moencks et al., 2022). Operator assistance systems (OAS), such as exoskeletons, can increase productivity and reduce the ergonomic risk for employees. In the collected material, only (Weckenborg et al., 2022) model OAS. The authors integrate exoskeleton in an assembly line balancing problem. An interesting line of research would be to study the economic and ergonomic impacts of accounting for OAS in planning problems.

Ageing workforce. This topic is gaining more and more importance in the industry, due to a higher retirement age of the workforce (Calzavara et al., 2020). Older workers behave differently than younger ones, they have decreased physical and cognitive abilities, but more experience. These differences have impacts on decision models, for instance in terms of skill set, productivity, and rest break required. Few works in the collected material integrate these aspects (Berti et al., 2021; Battini et al., 2022), and more studies are needed to better adapt planning models to this population.

Collaboration with HF/E practitioners for models' validation. As the topic of this review is heavily influenced by HF/E, it is natural to highlight that an increment in collaborations between both disciplines would be beneficial: **(i)** First, to validate the relevance of the work of the OR community, and (ii) second, to guide the field toward modeling problems that are relevant in practice and the use of HAMs that make sense in a given situation. For instance, Ryan et al. (2011) study a production planning problem in a multidisciplinary approach. Insights are developed to guide the collaboration between OR and HF/E scientists. Moreover, it appears that it is sometimes challenging for an OR practitioner to work on real-life case studies. This will eventually raise the question of the validity of the work. Real-life applications provide opportunities and appropriate settings to validate OR work. Let us emphasize that this is even more critical in human-aware optimization due to its direct impact on humans. It would be beneficial to see more case studies where human-aware optimization models are implemented in industrial contexts, and the implications of such interventions are assessed. This kind of work could bring insightful feedback to the community and lead to new research directions guided by industrial needs. Substantial efforts have been made in this regard (Ryan et al., 2011; Yi and Chan, 2015; Bautista et al., 2016b; Battini et al., 2016a; Moussavi et al., 2019), but further work is needed. As a consequence, the amount of work using real-life data with risk assessment methods is scarce. It would be beneficial for the community to have access to datasets issued from fieldwork and collaborations with ergonomists. In this way, OR researchers could confront their work and solution methods to real data.

9. Conclusions

In the first part of this literature review, we have introduced the corpus of the reviewed material. It covers a large spectrum of classical logistics and manufacturing optimization problems, which shows the interest and continued need for designing human-aware models and solution methods. Pushed, in particular, by the sustainable development movement, human considerations are more and more involved in logistics and manufacturing systems, including: warehousing, vehicle routing, scheduling, production planning, and workforce scheduling and management. In the current part, we have studied the modeling systems of human aspects through the lens of mathematical programming, i.e.: Which HFs and how they are integrated into decision models from logistics and manufacturing fields? And, what is the impact induced by the integration of HFs into the available modeling approaches? Based on a cross-analysis of the current review, multiple opportunities for future research have also been discussed. Due to the broad scope of the study, the review methodology is *semi-systematic*, to keep the studied corpus of manageable size. As such, and despite our commitment of being as transparent as possible, the inclusion methodology is not fully reproducible, and thus constitutes a limitation of the work. The literature search is limited to papers published before the end of 2022, and more recent insightful works have been produced within this active research stream. The monitoring of the existing and emerging trends within the area constitutes an important research avenue for future research.

In the second part of this review (Prunet et al., 2024), we give a comprehensive presentation of the range of modeling frameworks found in the collected material dedicated to the representation and the quantification of both ergonomic risks and human characteristics. Each HAM is explained in detail, and links are made to its relevance in the industrial context.

CRediT authorship contribution statement

Thibault Prunet: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing. **Nabil Absi:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing. **Valeria Borodin:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing. **Diego Cattaruzza:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, 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.

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