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STATE-OF-THE-ART REVIEW

Practical factors in order picking planning: state-of-the-art classification and review

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ABSTRACT
Market trends such as globalisation, increasing customer expectations, expensive industrial land and high labour costs cause a need for efficient order picking systems in practice. However, managers often do not implement findings from academic research on order picking planning into practice because researchers hardly account for practical factors (e.g., high-level storage, human factors, pick vehicle properties) or make unrealistic assumptions in their solution algorithms. A state-of-the-art review of the scientific literature on order picking planning (1) identifies and classifies highly influential practical factors, (2) shows the impact of these practical factors on order picking performance, and (3) illustrates how existing order picking planning models should be elaborated to account for practical factors. This study contributes to close the gap between research and practice by guiding future researchers to further increase the practical applicability of their research results.

KEYWORDS
order picking methods; literature review; logistics; practical factors; warehouse design

1. Introduction

Complex market conditions, caused by e-commerce and globalisation, increased customer expectations, expensive industrial land and high labour costs, force warehouses to handle a large number of orders in short time windows (Azadeh, De Koster, and Roy 2019; Jaghbeer, Hanson, and Johansson 2020). These market trends put extra pressure on order picking (i.e., the retrieval of products in the warehouse to fulfil customer orders) and show a clear need for efficient order picking systems (Van Gils 2019).

The majority of academic literature on order picking systems typically considers low-level parallel pick-aisle layouts, minimising picker travel distance (e.g., Ratliff and Rosenthal (1983); Petersen and Aase (2004); Ho and Tseng (2006); Ho, Su, and Shi (2008); Van Gils et al. (2018a)). Despite the valuable academic contribution of these studies, there is still a large potential to increase the practical applicability of the

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proposed solution algorithms and decision support models. Past research focusses on rigour (i.e., coherent, logically developed theory, and the various dimensions of methodological and analytical validity that are necessary to test theory), which is a necessary, but insufficient condition to assure relevance in practice (Carter 2008). Therefore, managers often do not implement findings from academic research into practice and, at the same time, researchers often fail to account for perspectives of practitioners when producing and transferring knowledge (Bendoly, Donohue, and Schultz 2006; Carter 2008).

This study contributes to close the gap between research and practice by identifying and analysing practical factors that have a substantial impact on the planning and performance of picker-to-part order picking systems, but that are insufficiently considered in academic planning models (e.g., batching, zoning) (Van Gils et al. 2019b). No previous definition of a practical factor exists in literature. We thus define a practical factor as any factor encountered in practice that has an influence on the order picking process. This can range from physical conditions, such as pick vehicle properties, to for example psychosocial factors. We do not exclude the emergence of future new factors from practice and thus future research can identify new practical factors.

Despite opportunities to automate the order picking process (Bozer and Aldarondo 2018; Lee and Murray 2019; Jaghbeer, Hanson, and Johansson 2020), most dominant order picking systems in practice are still picker-to-part systems (De Koster, Le-Duc, and Roodbergen 2007; Calzavara et al. 2017; Van Gils et al. 2019a). High investment costs and the risk of interruptions in the order picking process during the implementation phase of automated systems may still discourage the use of such systems in practice (Briant et al. 2020). Furthermore, picker-to-part systems still outperform robots on flexibility as humans proved to react better to unexpected changes in the process, are flexible with respect to capacity, and can retrieve a large variety of products (Van Gils et al. 2019b). However, it should be noted that the majority of the identified practical factors in this study may also play an important role in automated warehouses and therefore this study can be a kick-start for future research on practical factors in automated systems.

A state-of-the-art review of existing literature is performed in order to identify, classify and analyse practical factors. The identification of practical factors started during a valorisation project, entiteld 'Smart Logistics Limburg', in which we had to reveal the needs and challenges of logistics companies in our region. In total 437 logistical companies have been visited during this project in the years 2015-2017, of which over a 100 warehouses. These warehouses varied in size, sector (e.g. spare parts, e-commerce, chemical products,..) and level of digitalization. The warehouse visits have been a starting point for this research, resulting in a better and efficient search throughout the literature and regular updates with new warehouse visits. Based on this combined approach of literature search and warehouse visits, we identify a series of nineteen practical factors.

The main contributions can be summarised as follows. First, a series of nineteen influential practical factors are identified and described. Furthermore, four categories are proposed to classify these practical factors. Second, the effect of these practical factors on order picking performance is analysed to illustrate the relevance of each factor. Third, this study illustrates the effect of each factor on modelling the planning problems and shows how to account for each practical factor in existing (and/or new) solution algorithms. Finally, the review provides insights into the implications of accounting for practical factors in planning problems for researchers and practitioners.

Although a wide range of literature reviews on planning order picking operations appeared, most of these reviews have been published more than a decade ago (De Koster, Le-Duc, and Roodbergen 2007; Rouwenhorst et al. 2000) or are dedicated to for example human factors in order picking (Grosse et al. 2015; Grosse, Glock, and Neumann 2017), planning problem combinations (Van Gils et al. 2018b), e-commerce challenges (Boysen, de Koster, and Weidinger 2019), warehouse systems for brick-and-mortar retail chains (Boysen, de Koster, and Füßler 2021) or robotised picking systems (Azadeh, De Koster, and Roy 2019). This literature classification significantly differs by providing the newest research articles thereby identifying the effect of practical factors in the context of planning problems for manual order picking and providing future research opportunities that enable the design of practically relevant decision support models.

The remainder of the paper is structured as follows. Section 2 outlines the scope of the review. Section 3 fulfils the first and second contribution by introducing and classifying the nineteen practical factors and analysing their effect on order picking performance. Section 4 provides the third contribution: the extent to which the practical factors impact modelling of planning problems and how to account for them in the respective solution algorithms. Finally, implications for both research and practice are discussed in Section 5 and future research opportunities are provided in Section 6.

2. Scope of the review

The scope of the review is summarised in Figure 1. On the left side of Figure 1, the main planning problems in picker-to-part order picking systems are categorised and ranked from strategic problems to operational issues. Table 1 defines all planning problems. For an extensive overview of order picking planning problems, the reader is referred to Rouwenhorst et al. (2000), De Koster, Le-Duc, and Roodbergen (2007) and Van Gils et al. (2018b). Strategic management decisions refer to policies and plans for using the resources in order to fulfil the long term competitive strategy. Examples of strategic decisions are the layout of the storage area (i.e., shape, number of warehouse blocks and depot location), as well as the selection of storage systems, in particular the level of automation and the material handling equipment to retrieve items. At the tactical level, decisions are taken that impact the medium term. The determination of the resource dimensions, like storage location assignment and the size of pick zones, are examples of tactical decisions. Finally, operational decisions typically concern daily operations like batch formation and job assignment. Decisions of operational nature should be considered within the constraints set by the strategic and tactical decisions. The nineteen practical factors that are identified based on warehouse visits and academic literature are illustrated on the right side of Figure 1. Four sub categories are proposed to classify these practical factors into: system factors, human factors, product and order factors and inventory factors. An in depth discussion of the practical factors can be found in Section 3.

Based on the framework of Figure 1, articles that analyse at least one of the defined order picking planning problems and account for at least one of the identified practical factors are selected. Consequently, the scope of the review is restricted to articles that examine multiple policies (i.e., solution methods or techniques for organising a planning problem) for at least one planning problem (Van Gils et al. 2018b) and account for at least one of the nineteen practical factors. For example, a study testing multiple routing methods (e.g., traversal, largest gap and optimal routing) and evaluating the effect of picker blocking (i.e., practical factor) is included in the overview, whereas articles assuming a single and fixed routing method in combination with picker block-

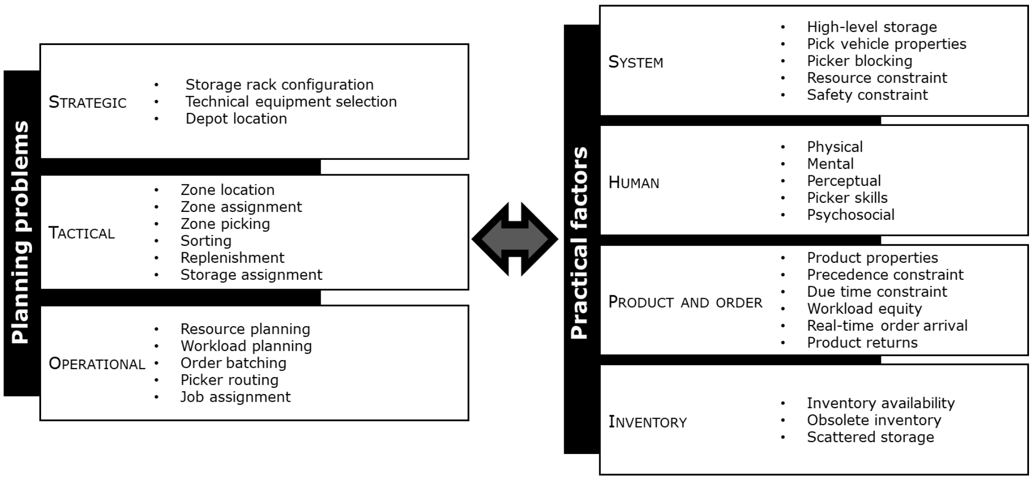

Figure 1. Scope of the review

ing are excluded from the review since these studies are not able to provide insights into the effect of the practical factor on modelling and solving the respective planning problem. Furthermore, articles optimising order picking in a theoretical context, such as minimising travel distance in low-level picking systems (Ratliff and Rosenthal 1983; Theys et al. 2010), as well as articles that only analyse a practical factor in the context of warehouses (i.e., not account for them in order picking planning) such as safety antecedents (De Koster, Stam, and Balk 2011; De Vries, De Koster, and Stam 2016c), are excluded from the classification; despite the academic contribution, these studies are unable to provide insights into the effects of practical factors on modelling and solving order picking planning problems.

The scope is further delimited by publication quality criteria. Only research articles published in English-language journals with an Impact Factor of at least 1.0 (based on the Impact Factors of 2019 by Thomson Reuters) are selected. Books and conference proceedings are excluded from the analysis, as these studies are often preliminary versions of journal publications. This results in a set of 119 research articles. This pool of articles is used to analyse the effect of practical factors on the planning of order picking operations. Figure 2 demonstrates the distribution of the article pool over time. The time distribution illustrates a strongly increased number of articles accounting for practical factors in recent years, showing that practical factors are inevitable when optimising order picking operations.

Our literature review strongly differs from earlier surveys in warehousing. Note that reviews on automated or robotic order picking systems are excluded from this discussion as the article overlap with our review would be negligibly small. Previous literature reviews on warehouse operations focus on individual planning problems such as warehouse design, storage assignment, batching and routing (De Koster, Le-Duc, and Roodbergen 2007), stochastic models for warehouse operations (Gong and De Koster 2011) or investigate the combination of tactical and operational planning problems (Van Gils et al. 2018b) but do not consider practical factors in their analysis. The study of Boysen, de Koster, and Weidinger (2019) is dedicated to warehouse systems especially suited for e-commerce retailers. Warehousing systems are evaluated

Table 1. Order picking planning problems

Planning problem	Description
Strategic	
Storage rack configuration	Determining the width and height of storage racks, as well as the length and width of pick aisles and cross-aisles, given the size or capacity requirements of the pick area (Thomas and Meller 2015)
Technical equipment selection	The usage of technological tools (e.g., material handling equipment, pick by voice) to facilitate picking (De Vries, De Koster, and Stam 2016b)
Depot location	Deciding on the number of depots and the location of the pick-up and delivery point to start and end each pick tour (Cortés et al. 2017; Diefenbach and Glock 2019)
Tactical	
Zone location	How to split the order pick area into pick zones (i.e., number of zones, the location of zones and the zone shape) (Jane and Laih 2005)
Zone assignment	How to allocate products to pick zones, either based on product properties (e.g., size weight, safety and temperature requirements) or demand properties (e.g., customer type) (Jane 2000)
Zone picking	The flow of customer orders through all pick zones, which can be in parallel or sequential (Parikh and Meller 2008)
Sorting	Consolidating and sorting products, either during the pick tour (sort-while-pick) or after picking (pick-and-sort) (Van Nieuwenhuyse and De Koster 2009)
Replenishment	Deciding on how and when to refill storage locations in the order pick area (Gagliardi, Ruiz, and Renaud 2008)
Storage assignment	Rules on how to allocate products to either individual storage locations or (turnover based) storage classes (Brynzér and Johansson 1996)
Operational	
Resource planning	Determining the resource level and allocating the available resources across order pick areas (Van Gils et al. 2017)
Workload planning	Which customer orders to retrieve during which time period (Vanheusden et al. 2020b)
Order batching	Rules on which customer orders to combine in each pick tour (Henn 2012)
Picker routing	Sequencing storage locations that should be visited in each pick tour to retrieve all products on a pick list (Van Gils et al. 2019b)
Job assignment	Deciding on the sequence in which orders/batches of orders are retrieved, as well as the assignment of these (batches of) orders to the available pickers (Henn 2015)

and their suitability for e-commerce operations are discussed. Therefore, the study of Boysen, de Koster, and Weidinger (2019) significantly differs from the current review as both aim and scope of the study are different.

The following literature reviews are more closely related to the current review as they mention or discuss several practical factors in warehousing. The studies of Grosse et al. (2015) and Grosse, Glock, and Neumann (2017) stress the need to account for human factors in planning order picking operations. These literature reviews state that humans can be characterised by their physical, mental, perceptual and psychosocial state. Because the current review considers picker-to-part systems, the classification of Grosse, Glock, and Neumann (2017) is used to describe human characteristics and

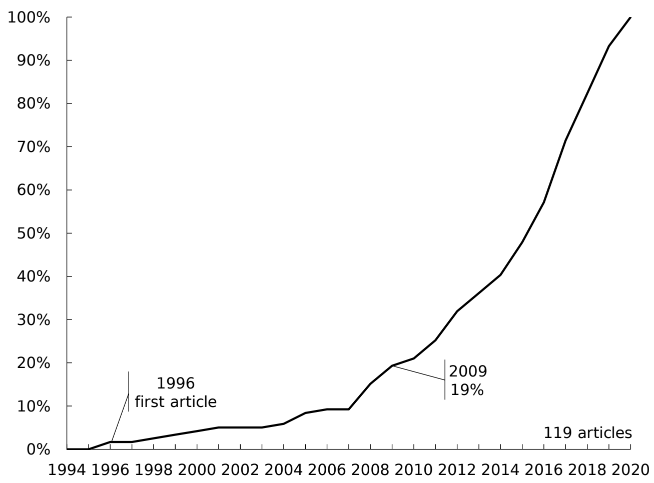

Figure 2. Cumulative time distribution of the article pool.

extends this classification with picker skills. Besides human characteristics, our literature review also discusses system characteristics, product and order characteristics, and multiple inventory characteristics. The study of Masae, Glock, and Grosse (2020) gives an overview of order picker routing policies with a strong focus on routing algorithms. They intend to increase the use of these routing algorithms in practice and therefore mention several practical factors that may influence the use of these routing algorithms in practice (e.g., aisle characteristics, human factors, capacity and resource constraints). Our literature review has a much broader scope in two ways: (1) a systematic review is performed of all considered practical factors, thus leading to an exhaustive list of factors (e.g., safety constraints, product properties, product returns), and (2) the importance and influence of practical factors is discussed in a broader context (i.e., all strategic, tactical and operational order picking planning problems) rather than only picker routing.

3. Impact of practical factors on order picking performance

The complex nature of order picking operations, caused by the large number of planning problems and resulting relation among these planning problems (Van Gils et al. 2018b), requires decision supporting tools to manage operations efficiently and effectively. In academic literature, often assumption-restricted models (i.e., making many or unrealistic assumptions) that insufficiently account for practical factors are proposed. These assumption-restricted models are less complex and therefore easier to solve. When developing models, a trade-off often needs to be made between reflecting reality in the model and being able to solve the model in a reasonable time. However, accounting for practical factors results in large opportunities to further increase the practical applicability and predictive accuracy of these models and solution algorithms (Cortés et al. 2017).

In Sections 3.1 to 3.4 each practical factor from Figure 1 is described. The impact of each of the practical factors on order picking performance is analysed and summarised in Table 2. The order picking performance measures in Table 2 are based on the extensive literature review that was carried out in this paper. The performance measures that were used in the discussed papers are inserted in Table 2. If a combina-

Table 2. Impact of each practical factor on order picking performance measures.

	Efficiency	Storage capacity	Service level	Accidents	Worker well-being
System factors					
High-level storage	•	•			
Pick vehicle properties	•				
Picker blocking	•			•	•
Resource constraint			•		
Safety constraint	•			•	
Human factors					
Physical	•				•
Mental	•				
Perceptual	•		•		
Psychosocial	•		•		•
Picker skills	•		•		
Product and order factors					
Product properties	•	•	•		
Precedence constraint	•		•	•	
Due time constraint			•		
Workload equity	•		•		•
Real-time order arrival	•		•		
Product returns	•	•			
Inventory factors					
Inventory availability	•		•		
Obsolete inventory	•	•			
Scattered storage	•	•			

tion is not indicated in the table, this means that no paper of our review examined this combination. This does not imply that this combination is not relevant in practice. Practical factors found in the investigated articles impacted order picking efficiency, storage capacity, service levels, accidents and worker well-being. Efficiency is about making the best possible use of resources with the least waste of time and effort as possible (Van Gils et al. 2018b). Storage capacity is defined as the number of products that can be stored per square meter (Van Gils et al. 2019b). Storage capacity can for example either be increased (e.g., introducing narrow aisles or opt for high-level storage) or managers can ensure a more efficient use of current storage (e.g., optimise assignment of possible heterogeneous products to locations, introduce methods such as scattered storage or rethink the return policy of the warehouse. Service level is defined as the timely delivery of the correct items to the customer (Gong and De Koster 2008; Henn and Schmid 2013; Giannikas et al. 2017; Van Gils et al. 2017). In the context of warehouse safety, the risk on accidents during order picking between pickers and pick vehicles needs to be evaluated (De Koster, Stam, and Balk 2011; Hofstra et al. 2018). Finally, the importance of the physical and mental well-being of order pickers should not be neglected while optimising order picking operations (Grosse et al. 2015).

3.1. *System factors*

System factors are defined as generally existing attributes of order picking systems in practice that are typically fixed in the short term due to strategic decisions such as layout design and system selection. However, tactical and operational planning problems should account for system factors in order to benefit from these strategic decisions. The following system factors can be identified: high-level storage, pick vehicle properties, picker blocking, resource constraint and safety constraint.

3.1.1. High-level storage

Companies need to store a large variety of products into their warehouses to satisfy customer demand. As industrial land is very expensive and storage capacity requirements are high, companies often opt for *high-level storage* systems to be able to store more products per square meter (Van Gils et al. 2019b). Storage racks in high-level storage systems consist of multiple levels, storing multiple products in a single storage rack section, in contrast to low-level storage systems (i.e., single-level storage rack sections). In addition to horizontal travel along pick aisles and cross-aisles, high-level storage systems require order pickers to travel vertically to retrieve products from storage locations at higher levels (i.e., pick truck lifting), affecting total travel time (Pan, Wu, and Chang 2014).

3.1.2. Pick vehicle properties

Pick vehicle properties can impose challenges in order picking planning in two different ways. First of all, warehouses have a set of heterogeneous pick vehicles available to perform the activities in a warehouse. The number of each type of pick vehicle is limited and should therefore be accounted for in order picking planning. Assuming a homogeneous pick fleet in solution algorithms may lead to infeasible solutions as different types of pick vehicles can have different capacities, travel speeds and/or lift heights (Cortés et al. 2017). For example, batch capacities can be violated for certain pick vehicles or proposed storage locations cannot be reached due to a restricted pick height of certain pick vehicles (Ballestín, Pérez, and Quintanilla 2017). Second, the typical linear distance-time relation strongly simplifies the real behaviour of pick vehicles. Pick vehicle acceleration and deceleration (Heath, Ciarallo, and Hill 2013), as well as making left-, right-, U-turns and driving backwards at a slower pace (Çelik and Süral 2016) is expected to substantially affect travel time and consequently order picking efficiency (Wen, Chang, and Chen 2001).

3.1.3. Picker blocking

Pickers can block each other while picking in the same region of the order picking system (Pan and Wu 2012). Multiple pickers operating concurrently in the same order pick area inevitably cause wait times and increases the risk on accidents (Van Gils et al. 2019b). *Picker blocking* causes idle time for order pickers, increasing the total order picking time (Parikh and Meller 2008, 2009). Moreover, blocking increases health risks in the warehouse as pickers work in close proximity, which is especially relevant during a pandemic. Two types of picker blocking have been identified in the literature. First, storage rack blocking means pickers cannot reach demanded products because another picker is retrieving products at the respective storage rack. Second, in-the-aisle blocking is mostly caused by narrow aisle picking (Van Gils et al. 2019b). Despite the benefits of narrow aisles (dense storage of products, increased total capacity, reduced travel times compared to wide aisles), it frequently results in picker blocking as pickers cannot overtake each other. Storage rack blocking can be an issue in both wide aisle and narrow aisle warehouses due to a growing number of order pickers (Mowrey and

Parikh 2014).

3.1.4. Resource constraints

Resources, such as space, labour, and equipment, need to be allocated among the different warehouse functions, including order picking (Gu, Goetschalckx, and McGinnis 2007). Although resource capacity drives the service quality to customers and resulting order picking performance, labour and equipment resources are mostly assumed to be infinite in literature (Van Gils et al. 2017). However, resource capacity is limited in practice and customer orders can only be retrieved by the available resources, such as order pickers (Ardjmand et al. 2018; Van Gils et al. 2019a).

3.1.5. Safety constraints

Despite the large number of accidents that happen in warehouses (De Koster, Stam, and Balk 2011; Hofstra et al. 2018), *safety constraints* are not considered sufficiently when optimizing order picking operations. Safety rules, such as prohibiting truck backing to avoid that retrieved products fall on the picker, ensure the safety of individual order pickers (Chabot et al. 2018). Time pressure is high and pick trucks work in close proximity, resulting in an enhanced risk of accidents involving multiple order pickers (De Koster, Stam, and Balk 2011; De Vries, De Koster, and Stam 2016c). Traffic rules, such as limiting the number of pickers within aisles, imposing one-way traffic directions within aisles, and prohibiting vehicle turns, prevent routes from crossing which reduces the risk of accidents, but increases travel time and resulting picking efficiency (Çelik and Süral 2016; Ballestín, Pérez, and Quintanilla 2017; Van Gils et al. 2019b). Furthermore, chemical properties of SKUs can induce additional safety risks because of potential chemical reactions that can occur (Vanheusden et al. 2020a).

3.2. *Human factors*

Humans are the central actors, especially in manual order picking systems. The incorporation of human factors in order picking planning is highly relevant in practice. Order pickers may pick the wrong product or an incorrect number of these products. These mistakes can have a significant impact on order picking performance, resulting in delivery delays, financial losses and lower customer satisfaction (Grosse, Glock, and Neumann 2017). Ignoring human-system interactions thus results in an incomplete picture of real-world order picking, resulting in unnecessary losses (Grosse et al. 2015). Human factors are defined as the factors that determine the unique behaviour of human pickers (Bendoly, Donohue, and Schultz 2006). This behaviour is typically different for each individual picker, differentiating humans from automated or robotised systems. Grosse et al. (2015) are the first to differentiate order pickers based on the following factors: physical factors (e.g., posture), mental factors (e.g., learning), perceptual factors (e.g., human information processing) and psychosocial aspects (e.g., motivation or stress), as these factors directly impact the performance of a warehouse (Grosse et al. 2015). We add individual picker skills (e.g., skill to drive a pick truck) as human factor to this classification as this also directly impacts the performance (Matusiak, De Koster, and Saarinen 2017).

3.2.1. *Physical*

The *physical* factor needs to be accounted for in order picking planning due to the labour intensive nature of order picking. Manual order picking may involve lifting heavy products and pushing or pulling pick devices. Since the job can be physically exhausting, it often leads to the development of musculoskeletal disorders (MSDs). Almost half of all work-related illnesses can be attributed to MSDs, with lower back pain being the most common injury (Grosse et al. 2015; Grosse, Glock, and Neumann 2017). Order picking operations are subject to high ergonomic risks because of unnatural postures (e.g., lifting and lowering), frequently repeated tasks, handling heavy and inconvenient products, or working under extreme temperature conditions (e.g., food industry) (Otto et al. 2017). Physical aspects reduce pick efficiency because the energy expenditure of human pickers increases (Calzavara et al. 2017, 2018).

3.2.2. *Mental*

The repetitive nature of order picking tasks induce learning effects of pickers over time. This aspect is defined as the *mental* factor. Prior literature typically assumes all order picking time components to be independent from the picker who performs the task. This simplification is problematic as individual human learning significantly impacts the efficiency of order pickers. Learning as a result of gaining familiarity with the products and order picking system comes up in most order picking time components (e.g., searching the right storage location and correct product, finding the shortest pick route) (Batt and Gallino 2019; Grosse, Glock, and Jaber 2013). Repeating a task multiple times results in a reduced time to fulfil the task in conformance with a learning curve, describing the progress of individual humans (Grosse, Glock, and Jaber 2013). While in industrial settings learning curves are often used, the usage of these curves in order picking planning models is rather limited (Grosse, Glock, and Neumann 2017).

3.2.3. *Perceptual*

Different from automated systems, human pickers have unique characteristics in translating information into concrete actions. This *perceptual* factor includes for example the conversion of information on the pick lists to visiting the correct storage locations and retrieving the correct product (Battini et al. 2015b). Human information processing affects both efficiency (Battini et al. 2015b) and pick quality (Brynzér and Johansson 1996).

3.2.4. *Psychosocial*

Psychosocial factors link to the mental well-being of employees. Due to the labour intensive and repetitive nature of the order picking job, pickers are often subject to stress, lack of motivation or even boredom. Ignoring psychosocial factors in order picking not only leads to reduced quality and efficiency but also results in absenteeism which is very costly for a company (Grosse et al. 2015).

3.2.5. *Picker skills*

Individual employee *skills* and capabilities significantly impact the order picking efficiency. Although order pickers receive similar training sessions at the start of their picking career, pickers differ in their physical and mental skills. This results in pickers that have varying skills in for example driving pick vehicles, handling heavy products and stacking products on pallets or in roll cages. Incorporating varying order picker skills in planning problems for manual order picking can improve the model predictability. Planning models should be able to find the best fit between an order picking job and the individual picker in order to benefit from these varying skills for each individual picker and positively impact picking efficiency and quality (Matusiak, De Koster, and Saarinen 2017).

3.3. *Product and order factors*

Product and order factors contain practical factors related to the type of products that are collected and specific order information. Solution algorithms ignoring these factors related to both orders and products often provide solutions that lack effectiveness since they are mostly infeasible in practice. Consequently, these models overestimate the real order picking performance. For example, a routing policy that creates routes that do not account for product properties such as weight or size, are hard or even not able to be executed in practice because of incorrect stacking of products on the pick cart. Furthermore, precedence constraints, due time constraints, workload equity, real-time order arrival and product returns may further limit proposed solutions in practice.

3.3.1. Product properties

Product properties such as weight, size, and temperature conditions limit the allocation of products to storage locations as not all products are allowed at all locations (Chabot et al. 2017; Dekker et al. 2004; Vanheusden et al. 2020a). Moreover, varying product properties result in varying retrieval times at storage locations and different handling methods: retrieving large and heavy products requires substantially more time than small and light products (Jane and Laih 2005). In contrast to strongly varying product properties, the negative consequences of highly similar products is insufficiently accounted for in academic planning models, as pointed out during interviews with several warehouse managers. The storage of highly similar products, such as shoes of different sizes, could be subject to substantial pick errors and longer search times at storage locations.

3.3.2. Precedence constraints

Precedence constraints are introduced because certain products should be retrieved before other products due to weight, fragility, shape and/or size restrictions, or because of customer's preferences. Most studies assume homogeneous products and no customer's preferences and thus ignore precedence constraints (Matusiak et al. 2014; Žulj et al. 2018). To avoid additional product handling during or at the end of a pick tour, and to avoid possible accidents during picking due to unstable stacking of products on the pick cart, the imposed precedence constraints should be accounted for when planning order picking operations (i.e., by for example retrieving heavy products before light products) (Žulj et al. 2018). Precedence constraints may result in longer travelling compared to a pick system without precedence constraints, but avoid additional sorting or damaging of products.

3.3.3. Order due time constraints

Customer orders are constrained by due times to be shipped on time. As accuracy in delivery times is an essential performance indicator for warehouses (Wruck, Vis, and Boter 2017), respecting *due time constraints* while planning picking operations is a critical issue (Çeven and Gue 2015). Most studies aim at minimizing total tardiness of all customer orders (i.e., the positive difference between the order due time and the batch completion time to which the order is assigned) (Chen et al. 2015; Scholz, Schubert, and Wäscher 2017) or ignore due times of orders (De Koster, Poort, and Wolters 1999; Henn and Wäscher 2012). These solution algorithms often provide a solution in which one or more customer orders will be picked after the picking due time, resulting in orders that miss the shipping deadline (Henn and Schmid 2013). In practice, such solutions may not be accepted by most warehouses, as this reduces the customer service level. Rather than accepting tardiness, the resource capacity will be increased (e.g., by shifting workers from other departments) to prevent orders being picked after due time. Note that respecting due times in planning models does not guarantee that all order are being shipped on time. Tardiness may occur due to unforeseen circumstances, such as technical defects or unavailable inventory (Van Gils et al. 2019a).

3.3.4. Workload equity

Managers have difficulties in managing order picking operations as hourly fluctuating demand, planning uncertainties, and the introduction of several order picking policies may result in an irregular workload. Allocating workload in an equitable manner over pick areas, order pickers or time periods is a difficult task in practice and if not considered carefully in planning order picking operations, workload peaks may appear. This may result in pick errors due to high work pressure and a higher probability of missing deadlines (Vanheusden et al. 2020b, 2021). The labour-intensive operations and the strongly fluctuating demand for customer orders, require a flexible resource capacity in warehouses (Van Gils et al. 2017). Warehouse managers state that order pickers experience stress and fatigue in these situations. As a consequence, concerns about *workload equity* have gained increasing attention (Vanheusden et al. 2020b). Considering equitable workload allocations in warehousing can lead to several benefits: a better usage of bottleneck resources (e.g., pick trucks), increased worker moral and an increase in overall picking efficiency (Matl, Hartl, and Vidal 2017; Vanheusden et al. 2021).

3.3.5. Real-time order arrival

E-commerce allows customers to place orders at any time of the day. Given the short time periods for retrieving orders, customer orders are unknown at the beginning of the planning period. To deal with this *real-time order arrival*, academic planning models should be able to intervene pick cycles and update pick tours to include newly arriving orders. Including new orders after a pick cycle or even after a complete pick wave threatens the timely delivery of these orders because of the tight time windows to retrieve them, affecting customer service (Gong and De Koster 2008; Giannikas et al. 2017).

3.3.6. Product returns

The growing e-commerce market leads not only to an increase in smaller customer orders, but also to a significant increase in the number of returned products (Schrotenboer et al. 2017). Returned products are first checked in a depot. Next, these products should be returned to the storage location storing the particular product. In this way the product is available to be retrieved for another customer order (Schrotenboer et al. 2017). These *product returns* cause a flow of products from the depot to storage locations in addition to the regular order picking flow of products from storage locations to the depot to fulfil customer orders. A smooth product return flow can improve the efficiency and inventory management of the warehouse and increase the utilisation of warehouse capacity (Wruck, Vis, and Boter 2013).

3.4. ***Inventory factors***

Products are retrieved from storage locations in order to fulfil customer orders. Nowadays, warehouses experience a large variety in products, varying demand for those products, and have numerous ways of determining where products should be stored. The practical factors related to storage issues are categorised as *inventory factors*. The effects of inventory availability, obsolete inventory and scattered storage are discussed in this section.

3.4.1. Inventory availability

Inventory is generally assumed to be infinite, meaning that pickers can always retrieve the required number of items from a storage location. A limited *inventory availability*, which is typically the case in practice, conditions the feasibility of pick routes. If inventory is unavailable at a particular storage location, pickers should visit another location (in case of scattered storage) or products needs to be replenished from the buffer area before the product can be retrieved (Cortés et al. 2017).

3.4.2. Obsolete inventory

Obsolete inventory contains products that occupy storage locations and have a very low or no turnover rate. These products prevent new fast moving products from being stored in the order pick area. The storage of these very slow-moving or obsolete inventory products causes underutilization of available storage capacity in the pick area (Min 2009).

3.4.3. Scattered storage

Scattered storage, the assignment of a product to multiple storage locations or storing multiple products at a single location, is typically imposed by the limited capacity of storage locations in combination with high turnover rates of some products. Scattered storage may be valuable to warehouses to increase order picking performance (e.g, in case of picker blocking). Instead of assuming a single storage location for each product (as in the large majority of planning models in literature), scattered storage can be beneficial, requiring sufficient storage capacity. In case of small ordered quantities per product (e.g., e-commerce orders), items of a single product should be distributed all over the warehouse in order to benefit from scattered storage. The probability that a picker is close to one of the locations of the required products is large when the products are widely spread. To retrieve higher quantities of a product in a pick tour, products should be stored close to each other (Weidinger 2018).

4. Impact of practical factors on modelling order picking problems

This section analyses the impact of each practical factor on modelling order picking problems and how to account for the practical factors in existing solution algorithms. All relevant literature on planning problems that accounts for at least one practical factor is classified in Table 3. For every combination, the number of existing papers is given. Irrelevant combinations are indicated with a (-) and relevant combinations that are not yet examined are indicated with a (0). Based on this classification Figure 3 illustrates the distribution of the nineteen different practical factors across the reviewed articles. The numbers above the bar chart indicate the number of articles that consider a certain practical factor. Research accounting for practical factors is rather scarce, especially with respect to all available order picking literature and the majority of combinations between practical factors and planning problems are still non-existing. Resource constraints have received the most research attention, followed by picker blocking. The remaining practical factors have received little research attention. In the following sections (Section 4.1 to 4.4) only relevant combinations are discussed as not all combinations are meaningful. For example, a paper accounting for pick vehicle properties may consider both routing and depot location (i.e., the paper is added at two categories in Table 3). However, pick vehicle properties only impact the routing problem and therefore only the combination of pick vehicle properties and routing is discussed.

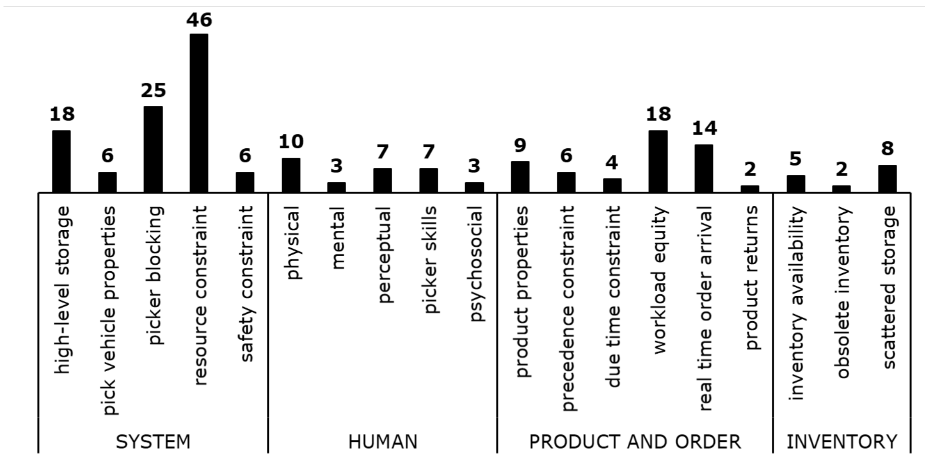

Figure 3. Distribution of the considered practical factors over the article pool (in number of articles)

4.1. *Research on system factors*

Following sections provide an in-depth discussion of the main research results for each of the five system factors. Combinations among system factors and planning problems can be found in Table 3.

Table 3. Classification of articles analysing at least one planning problem and one practical factor (in number of articles).

	Strategic			**Tactical**				**Operational**						
	Rack configuration	Technical equipment	Depot location	Zone location	Zone assignment	Zone picking	Sorting	Replenishment	Storage assignment	Resource planning	Workload planning	Order batching	Picker routing	Job assignment
System factors														
High-level storage	11	0	1	2	-	-	-	-	7	-	-	7	10	1
Pick vehicle properties	2	0	1	1	-	-	0	-	3	-	-	2	6	1
Picker blocking	6	-	-	2	0	7	1	-	11	0	-	5	10	9
Resource constraint	8	-	1	7	-	9	2	-	15	2	1	19	18	21
Safety constraint	4	-	0	1	-	-	-	-	2	-	-	3	6	1
Human factors														
Physical	5	1	1	1	-	-	-	-	7	-	0	-	-	0
Mental	-	0	-	1	-	-	-	-	1	0	-	0	1	1
Perceptual	-	6	-	-	-	-	-	-	1	-	-	-	-	-
Psychosocial	-	1	-	-	-	2	-	-	-	0	0	-	1	-
Picker skills	-	-	-	-	-	6	-	-	1	0	-	2	1	7
Product and order factors														
Product properties	3	-	1	-	1	-	0	-	4	-	1	1	5	1
Precedence constraint	1	-	-	-	0	-	-	-	3	-	-	1	6	-
Due time constraint	1	-	-	-	-	-	-	-	1	-	2	2	1	1
Workload equity	-	-	-	2	1	10	-	-	1	0	2	6	-	9
Real-time order arrival	1	-	-	1	-	-	1	-	2	-	0	13	6	4
Product returns	-	-	-	-	-	-	-	0	0	-	0	1	1	-
Inventory factors														
Inventory availability	-	-	1	1	-	-	-	2	2	-	-	-	2	-
Obsolete inventory	1	-	-	-	0	-	-	-	1	-	-	-	-	-
Scattered storage	-	-	-	-	-	-	-	1	3	-	-	1	5	1

4.1.1. High-level storage

Most research efforts have been on systems in which travelling is only done in two dimensions (i.e., low-level storage systems). Until now, 18 articles consider high-level storage systems in manual order picking (Figure 3). High-level storage is mostly included in papers dealing with rack configuration, storage assignment, batching and routing. Some of the papers account for high-level storage and integrate or combine multiple planning problems at once (Chabot et al. 2018; Van Gils et al. 2019a,b). Accounting for high-level storage directly impacts the routing problem and storage assignment decisions.

Solution algorithms for the routing problem should account for pick truck lifting. Lifting is typically very slow compared to horizontal travel and the speed of horizontal travel may depend on the vertical level of the truck. The length, width and number of aisles will impact horizontal travel distance, while the levels in a storage system directly impact vertical travel distance (Thomas and Meller 2015). The study of Clark and Meller (2013) uses the Chebychev metric to measure vertical travel in narrow aisle warehouses. The pick truck is able to move both horizontally and vertically and therefore the within-aisle travel time will be equal to the maximum of the horizontal travel time and vertical travel time. Thus, travel time is not linearly related to travel distance.

Next, the storage location assignment problem is directly influenced. High-level storage locations require the distribution and assignment of products among the different levels of the storage racks (Pan, Wu, and Chang 2014; Chan and Chan 2011), thereby considering that a substantial amount of lifting time is needed to reach the highest storage locations. Only if higher levels are used as storage and replenishment locations and lower levels (i.e., floor locations) for picking, the impact of high-level storage systems on travel time is negligible: vertical travel is limited to the replenishment of a pick location, while picking is performed on floor locations requiring only horizontal travel (Van Gils et al. 2019b).

4.1.2. Pick vehicle properties

Pick vehicle properties are accounted for in six articles on order picking planning and only take up a small portion of the literature accounting for system factors (Figure 3). These articles study the effect of pick vehicle properties within rack configuration, depot location, zone location, routing, batching, storage assignment and job assignment (Table 3).

Heterogeneous pick vehicles mainly impact the modelling of storage assignment and job assignment planning problems. As not all pick vehicles are able to access all pick locations, additional constraints are needed to ensure that items can be picked with a particular pick vehicle. These constraints either enforce items to be stored at other locations or make sure jobs are assigned to other pick vehicles (Ballestín, Pérez, and Quintanilla 2017). Moreover, when batching orders, batch capacity constraints can be adaptable per pick vehicle type to model different load capacities of the pick fleet (Cortés et al. 2017).

The majority of articles integrate pick vehicle properties into the routing problem. Travelling is widely used as surrogate for order picking efficiency, thereby assuming travel time to be directly proportional to the covered distance. In practice, travel time does not only depend on travel distance, as pick routes consist of a large number of stops, (narrow) pick-aisles need to be entered and left with pick vehicles and pick vehicles typically work in close proximity. Travel time is thus influenced by the number of turns (i.e., decrease in speed of 80% while turning) (Çelik and Süral 2016). Constraints should be included into the routing problem when turning a pick vehicle in narrow aisles is not possible (Heath, Ciarallo, and Hill 2013). A pick vehicle can then move backwards out of the narrow aisle, followed by a turn in the cross-aisle, which is substantially slower than forward velocity (Van Gils et al. 2019b). Moreover, pick vehicles slow down and eventually stop when they get close to a requested item and need a certain acceleration distance before they are back at full speed. Only the study of Heath, Ciarallo, and Hill (2013) includes acceleration and deceleration in manual order picking systems, in contrast to literature on robotic systems, in which acceleration and deceleration of lifts and vehicles is often included (Zou et al. 2018). A reason for this might be the deterministic robot's movement time. In manual systems, acceleration and deceleration does not only depend on the currently loaded products on the pick vehicle and other pick vehicles in close proximity, but also depends on the operator in charge of the pick vehicle.

4.1.3. Picker blocking

Including the idle time caused by picker blocking is of growing interest in academic research in the last ten years. As shown in Figure 3, a total of 25 articles consider picker blocking, making this the second most investigated practical factor. Ignoring the effect of picker blocking would lead to models that predict unachievable performances and cost expectations for the warehouse (Heath, Ciarallo, and Hill 2013).

Wait times resulting from blocking should be included as performance metric when modelling and evaluating zone picking, storage, batching and/or routing policies. Zoning states that pickers can only travel in a limited number of pick aisles during each pick tour and therefore wait times due to picker blocking shrink (Van Gils et al. 2019b). Some storage assignment strategies on the other hand, cause more picker blocking than others. For example, if a warehouse stores all fast moving products in the same zone, often close to the depot in order to decrease travel distance, picker blocking causes higher wait times in these respective aisles (Franzke et al. 2017). Dividing orders into batches in order to minimise travel distance may lead to less picker blocking. Pickers performing efficient batches visit storage locations in close proximity and thereby covering a smaller area in each pick tour (Hong, Johnson, and Peters 2012). Furthermore, safety regulations, often modelled as safety constraints by means of traffic rules within routing, can induce picker blocking. For example, the number of pickers simultaneously allowed in the pick aisle is limited because of safety considerations. If the maximum number of pickers in the aisle is reached, pickers have to wait at the entrance of the aisle, causing blocking in the cross-aisles (Hong, Johnson, and Peters 2012). These effects can strengthen or diminish depending on which combinations or integrations of planning problems are considered (Van Gils et al. 2018a,b, 2019b).

4.1.4. Resource constraint

A total of 46 research articles constrained the number of resources in the proposed decision support models (Figure 3). Resource constraints gain popularity in research moving from long term to short term planning. In layout related problems (e.g., rack configuration, depot location and zone location), particular order picking layouts are subject to congestion if a certain resource threshold is exceeded. Considering a constraint on the number of resources becomes even more important while batching orders, routing pickers, and assigning jobs to pickers: operational planning problems which are often integrated due to their strong relation (Van Gils et al. 2019a). A wide range of heuristic algorithms have been developed that solve the integrated problems thereby limiting the available resources (Henn 2015; Chen, Wei, and Wang 2018; Scholz, Schubert, and Wäscher 2017; Matusiak, De Koster, and Saarinen 2017; Ardjmand et al. 2018; Van Gils et al. 2019a). Only two articles introduce methods that propose how to plan and manage resources (Kim, Dekker, and Heij 2018; Van Gils et al. 2017). Regression models turn out to be very effective in defining the number of resources (Kim, Dekker, and Heij 2018; Van Gils et al. 2017).

4.1.5. Safety constraint

De Koster, Stam, and Balk (2011) are the first to raise attention for the large number of warehouse accidents by exploring the antecedents of warehouse safety. Van Gils et al. (2019b) identify safety constraints as a promising and necessary avenue for future research in the optimisation of order picking planning. A total of six articles consider safety constraints, especially in the routing problem (Figure 3 and Table 3). Safety constraints are often guided by traffic rules. These traffic rules prevent routes from crossing, thereby reducing the risk of accidents (Çelik and Süral 2016; Ballestín, Pérez, and Quintanilla 2017). Safety included as constraint is necessary to create feasible routes and accurately model practice (Ballestín, Pérez, and Quintanilla 2017). Different variants of safety constraints have been proposed in literature, including penalising vehicle turning (Çelik and Süral 2016), prohibiting trucks moving backwards (Chabot et al. 2018), forcing horizontal movements at ground level (Chabot et al. 2018), limiting the number of pick vehicles working concurrently in a pick aisle (Ballestín, Pérez, and Quintanilla 2017; Van Gils et al. 2019b; Chen, Xu, and Wei 2019), and forcing one-way travel directions (Briant et al. 2020).

4.2. *Research on human factors*

In the following sections, an overview of the most important research results is provided for combinations of each human factor class and existing planning problems in manual order picking. An overview of the combinations can be found in Table 3.

4.2.1. Physical factor

The physical factor (i.e., ergonomics) is the most studied topic in literature on human factors in warehousing with a total of 10 articles (Figure 3). Physical aspects are mainly accounted for in storage assignment decisions and in papers studying varying rack configurations (Table 3). Sadiq, Landers, and Don Taylor (1996) are the first to account for physical factors in storage assignment, forcing heavy weight items to be stored at the most ergonomically desirable locations. This golden-zone storage (Petersen, Siu, and Heiser 2005), referring to locations between the picker's shoulder and waist, results in reduced total fulfilment times as workers use less time to retrieve items inside the golden zone. Other storage assignment methods (Battini et al. 2016; Larco et al. 2017; Calzavara et al. 2018; Diefenbach and Glock 2019) do not only take into account economic goals (e.g., total fulfilment time, total cost), but also want to optimise the ergonomic environment of the picker and often simultaneously check for ergonomically viable rack configurations (Calzavara et al. 2017; Otto et al. 2017; Glock et al. 2019). It can be argued that the literature is not unanimous about how these ergonomic goals should explicitly be accounted for in order picking planning models in general. Battini et al. (2016) optimise ergonomic goals by using the concept of human energy expenditure, Diefenbach and Glock (2019) use the ergonomic strain of extracting items and Larco et al. (2017) use the concept of picker discomfort. These various methods for measuring the ergonomic perspective make it hard to compare results and make general conclusions and recommendations for warehouse management.

4.2.2. Mental factor

Grosse and Glock (2013) are the first to study learning effects in an order picking environment. The authors investigate which learning curves can describe the learning process most accurately and conclude that the the learning curves of De Jong (1957), Wright (1936), Dar-El, Ayas, and Gilad (1995) and the three-parameter hyperbolic model are most appropriate. Only three papers study learning effects in combination with storage assignment, zoning, routing and job assignment decisions (Figure 3).

Grosse, Glock, and Jaber (2013) study learning and forgetting in case of storage reassignment. Changing the storage assignment strategy results in the loss of acquired knowledge and will imply forgetting. In other words, a trade-off arises between the efficiency gained by the new storage assignment policy and the initial drop in productivity that will arise from forgetting. Grosse and Glock (2015) develop a mathematical model that gives decision support as to how workers should be assigned to warehouse zones depending on their different learning rates. Results show that it is beneficial to assign workers with the lowest learning rate in the workforce to the fastest moving zone to gain experience. Batt and Gallino (2019) analyse picker learning in case of scattered storage and study these learning effects in storage assignment, routing and job assignment. Scattered storage in this case, results in storage locations storing multiple types of products, which increases the search times for identifying the correct product. However, the negative effect of increased search times diminish if an order picker evolves from novice to experienced picker, the variance in learning performances between pickers drops with experience and productivity can be improved by strategically assigning orders across pickers with varying experience.

4.2.3. Perceptual factor

Research on perceptual factors in order picking looks for activities and tools that can improve, or at least stimulate faster and more correct human information processing (Grosse et al. 2015). Seven articles study perceptual aspects in planning problems for manual order picking (Figure 3). Six of these articles consider human information processing in combination with technical equipment such as pick-by-voice, pick-by-light or even the use of augmented reality technologies (Reif and Walch 2008; Reif and Günthner 2009; Reif et al. 2010; Schwerdtfeger et al. 2011; Yeow and Goomas 2014; Battini et al. 2015a) and a single paper introduces a storage assignment strategy that reduces the amount of information a picker needs during handling (Brynzér and Johansson 1996).

The most traditional way of order picking is with the use of paper pick lists (Yeow and Goomas 2014). Such systems are easy to implement in practice and straightforward to use. However, these paper pick lists are quite laborious for the picker and they do not stimulate reduction of pick errors. The effectiveness of several paperless picking systems (e.g., barcodes handheld, RFID tags handheld, voice picking, traditional pick-to-light, RFID pick-to-light) depends on the configuration of the warehouse (e.g., low-level vs multi-level picking) and the number of hourly picks (i.e., high, medium or low) (Battini et al. 2015a). Most of these paperless technologies still require a lot of handling as they require manual data entry into the device and are often not well accepted by pickers (e.g., pick-by-voice) (Reif and Walch 2008).

Augmented reality in order picking can improve the information visualisation by projecting relevant or important data into the worker's field of view by using head mounted displays (HMDs). Multiple graphical user interfaces and hardware for the HMDs are tested. Augmented reality definitely has potential to better guide pickers and reduce pick errors. Augmented reality systems also have interesting opportunities for training new order pickers (Reif and Walch 2008; Reif and Günthner 2009; Reif et al. 2010; Schwerdtfeger et al. 2011) .

4.2.4. Psychosocial factor

Preventing psychosocial risk in an order picking environment is not so straightforward in this globalised economy. The focus is often more on achievement and less on the well-being of employees. Table 3 shows the ignorance of academic literature towards the integration of psychosocial factors in planning order picking operations. Only three papers account for psychosocial factors (Figure 3).

De Vries, De Koster, and Stam (2016b) study the effect of individual characteristics (i.e., personality traits) on the use of paperless information technologies such as pick by voice, pick to light and RF-terminal picking in order picking by means of a field experiment. Insights of the study can be used to assign the right order picker to the right picking tool to lower warehouse costs and increase performance. De Vries, De Koster, and Stam (2016a) demonstrate how incentive systems can be used to increase the order picking productivity in different zoning settings while accounting for the regulatory focus of the order picker. For example, the study suggests that competition-based incentive systems work best in parallel zone picking systems with dominant promotion focussed order pickers.

Elbert et al. (2017) take into account the possible consequences of maverick picking in order to check which routing policy is most efficient. Maverick picking, defined as modifications in work flows by pickers, negatively impacts order picking operations. Order pickers may attempt to change imposed work schedules (e.g., routing through the warehouse) as given information seems complex, illogical or leads to confusion. However, even if pickers deviate from a given route, the optimal routing policy is still the best option in most scenarios.

4.2.5. Picker skills

A total of seven articles consider picker skills in planning problems for manual order picking (Figure 3). Most of this research shows the effect of varying picker skills in bucket brigade systems (picking system in which pickers progressively perform a set of operations), for which the variation in task times among workers is often studied and accounted for (Koo 2009; Webster, Ruben, and Yang 2012; Hong, Johnson, and Peters 2015; Hong 2018; Fibrianto and Hong 2019; Hong 2019).

Academic literature in industrial settings mostly focusses on the capabilities of workers instead of the skills. Capabilities state that a worker is capable of performing a task irrespective the time he/she needs. Skills on the other hand are time dependent. For example, all order pickers can be able to execute a certain batch, but batch execution times differ among order pickers (Matusiak, De Koster, and Saarinen 2017). In parallel zone picking systems, the speed of the entire system is determined by the speed of the slowest worker. To solve this problem, bucket brigades are introduced as an alternative to zone picking. Koo (2009) prove by means of simulation that zoned bucket brigade picking works better than zone picking especially in situations where order pickers have different work speeds. In most of the studies on bucket brigades, differences in skills (i.e., task times) are integrated or the differences in hand-off times and walking times between pickers are included (Webster, Ruben, and Yang 2012; Hong, Johnson, and Peters 2015; Hong 2018, 2019). Besides studies on bucket brigade systems, the study of Matusiak, De Koster, and Saarinen (2017) develops a model to solve the combined batching, routing and picker assignment problem including picker skills such as agility, strength of the order picker, pick height and the ability to pick large volumes. Batch execution times are forecast for individual pickers. Multilevel modelling is used to distinguish between-picker differences. Results state that if the sum of total order processing time is minimised, state-of-the-art batching and routing methods can be improved by almost 10% taking into account skill differences among pickers.

4.3. *Research on product and order factors*

The following sections provide an analysis of the impact of each of the six product and order factors on modelling and solution algorithms of the main order picking planning problems. An overview of the combinations can be found in Table 3.

4.3.1. Product properties

Physical characteristics of products influence the handling of the products, which mainly impacts the rack configuration, zoning, storage assignment and routing problem (Önüt, Tuzkaya, and Doğaç 2008; Diaz 2016; Ballestín, Pérez, and Quintanilla 2017; Cortés et al. 2017; Accorsi, Baruffaldi, and Manzini 2018). By ignoring varying product properties, solution algorithms produce unrealistic and often infeasible solutions in practice. Only nine articles consider this practical factor in order picking planning (Figure 3).

Starting with the most obvious product property, heterogeneity in size impacts the way racks are configured and products are assigned to storage locations. To optimise storage capacity, the volume of storage racks need to be divided into locations of different size when products vary in size and products need to be assigned to the best fit storage location in terms of size. Storing products at locations that are too large results in empty storage rack volume, while storing a product in a location that is too small is infeasible. Locations and products can be put into classes of different size and constraints in the model can force products to be stored only when there is a fit between the location and product class (Önüt, Tuzkaya, and Doğaç 2008). In a similar way other product properties, such as weight, fragility and turnover can be included into classes (Dekker et al. 2004; Diaz 2016; Önüt, Tuzkaya, and Doğaç 2008; Ballestín, Pérez, and Quintanilla 2017; Accorsi, Baruffaldi, and Manzini 2018).

Planning picker routes is subject to the effect of product properties as well. Varying product properties may impose precedence constraints when picking to ensure physical integrity of the retrieved products (Dekker et al. 2004; Cortés et al. 2017; Chabot et al. 2017). This effect is discussed in more detail in the next section.

Finally, zone picking can be efficiently applied to deal with varying product properties, thereby assigning similar products to one pick zone. This often results in productivity differences among pick zones due to different handling efficiency: the average productivity is low in pick zones storing heavy products, while zones storing smaller items are designed to maximise productivity. These differences in productivity should be accounted for when for example planning the workload (Vanheusden et al. 2020b).

4.3.2. Precedence constraint

Precedence constraints have been widely studied in VRP contexts, but received only little attention in other real-life applications such as warehousing. In an order picking context, precedence constraints make sure that some items are picked before others due to product properties, stackability, preferred unloading sequence or other specific customer requests that may limit the possible picking sequence and often do not allow for a near optimal sequence (Dekker et al. 2004; Matusiak et al. 2014; Žulj et al. 2018; Bódis and Botzheim 2018). Figure 3 shows that six articles consider precedence constraints in order picking optimisation.

To ensure the preferred precedence, routing policies can be adapted or the positioning of products can be adapted based on the behaviour of the routing policy (Dekker et al. 2004). In either way, this imposes constraints to the storage assignment or routing problem. Constraints have been proposed in several variants. Weight constraints make sure order pickers do not have to lift heavy items to high positions, increasing stability (Chabot et al. 2017; Bódis and Botzheim 2018; De Santis et al. 2018; Žulj et al. 2018). Fragility constraints make sure that fragile products are not placed under heavy items (Chabot et al. 2017). The category constraints make sure that non-food items are picked before food items to avoid food contamination (Chabot et al. 2017). Finally, order due constraints specify precedences per order due to group products in the stores of customers (Matusiak et al. 2014).

4.3.3. Due time constraint

In current literature, only four articles consider order due time constraints in order picking optimisation (Figure 3). Respecting due times is a critical issue especially in batching orders, routing pickers, job assignment and workload equity.

In the context of workload planning, models are constrained by deadlines of orders (i.e., order due times) (Vanheusden et al. 2020b). Çeven and Gue (2015) are the first to address the effect of wave forming times with daily transportation deadlines. Workload needs to be planned after orders have been released and before the shipment deadline (Wruck, Vis, and Boter 2013). Van Gils et al. (2019a) solve the integrated batching, routing and job assignment problem while ensuring all orders are picked before their due time. Order due times are included as hard constraints in the model in order to guarantee a high service level to customers.

4.3.4. Workload equity

Despite the attention for workload equity in various industries, research on workload equity in an order picking context stays limited. A total of 18 papers research workload equity in order picking planning (Figure 3), most of them on zone picking, order batching or job assignment (Table 3).

Warehouses are divided into zones to reduce travel distance, picker blocking and/or to make pickers familiar with the products in their respective zone (De Koster, Le-Duc, and Roodbergen 2007). By dividing the warehouse area in zones, issues on workload equity can arise between these zones due to varying pick densities across zones, resulting in workload imbalances. In order to balance the workload in the short run, the concept of bucket brigade systems is introduced (i.e., dynamic zone picking systems). In these bucket brigade systems, the use of sequential zone picking with flexible zone borders results in self-balancing systems for individual picker workload (Bartholdi, Eisenstein, and Foley 2001; Koo 2009; Hong 2014; Pan, Shih, and Wu 2015; Hong, Johnson, and Peters 2016; Hong 2018, 2019). Workload balancing in zoned systems in the long run can be achieved by varying the zone size and changing the product assignment to zones (Jane 2000; Jane and Laih 2005).

Before batches can be assigned to pickers, customer orders need to be assigned to pick waves (Vanheusden et al. 2020b). Vanheusden et al. (2020b) balance daily workload by evenly spreading the workload for each hour of the day. Several studies in bucket brigade systems have developed batching procedures to support a smoother workload (Pan, Shih, and Wu 2015; Hong, Johnson, and Peters 2016; Fibrianto and Hong 2019). Besides bucket brigade systems, workload equity impacts zoning (Van der Gaast, de Koster, and Adan 2018) and batch creation (Zhang, Wang, and Huang 2016; Huang et al. 2018) as well. Although workload imbalance in zone picking systems is proven to be larger compared to batch picking (Parikh and Meller 2008), studies analysing the imbalance in physical workload among pickers when creating and assigning batches are scarce. Kim (2020) introduce the concept of prioritising jobs before assigning them to pickers in order to manage workload and to face cut-off pressure.

4.3.5. Real-time order arrival

Figure 3 shows that 14 articles consider real-time order arrival in order picking optimisation. Real-time order arrivals mainly impact the operational decisions in order picking such as order batching, picker routing and job assignment (Table 3).

The large majority of research on real-time order arrival solves the batching problem (i.e., on-line batching) and adapts routing and job assignment policies to this changing environment. The impact of dealing with real-time order arrival on modelling the planning problems is limited. The main impact is on when the batching, routing an job assignment solution algorithms will be solved and which orders are considered. In a time window batching context, the batching, routing and job assignment are solved either after a fixed amount of time (i.e., fixed time window) or a fixed number of orders (i.e., variable time window) (Bukchin, Khmelnitsky, and Yakuel 2012; Xu et al. 2014; Van Nieuwenhuyse and De Koster 2009; Henn 2012; Chen, Wei, and Wang 2018; Pérez-Rodríguez, Hernández-Aguirre, and Jöns 2015; Zhang, Wang, and Huang 2016; Zhang et al. 2017). Once orders are batched, these batches cannot be interrupted, in contrast to dynamic order batching. In a dynamic policy, all orders assigned to a batch that have not been assigned to a picker are rebatched with newly arrived orders (Lu et al. 2016). Finally, an interventionist policy even allows newly arriving orders to be added to batches that are picked at the moment of solving the batching, routing and job assignment problems. In this last policy, the real-time order arrival can result in very small order throughput times (Giannikas et al. 2017; Van der Gaast, De Koster, and Adan 2019; Gong and De Koster 2008).

4.3.6. Product returns

Figure 3 shows that only two articles consider product returns in order picking optimisation. Schrotenboer et al. (2017) and Wruck, Vis, and Boter (2013) are the only ones that simultaneously consider the picking of customer orders and the delivery of returned products to storage locations. Batches and routes need to be created for the restocking of returned products in addition to the customer order picking flow. Taking into account product returns, increases overall workload and therefore results in an increase in the workforce level, which increases the probability of picker blocking.

4.4. ***Research on inventory factors***

Following sections analyse the impact of inventory factors on the modelling and solution algorithms of order picking planning problems. An overview of the combinations is shown in Table 3.

4.4.1. Inventory availability

Only five articles take the implications of storage availability into account as can be observed in Figure 3. The availability of inventory has implications within storage assignment (Pan et al. 2015) and picker routing (Cortés et al. 2017). Warehouses often choose to divide the storage area into two parts: a fast pick area and a buffer area.

An important research problem is to determine a product strategy that will guarantee product availability within the fast pick area (Anken et al. 2011). Gagliardi, Ruiz, and Renaud (2008) study this problem in a pick-to-belt environment and create multiple replenishment heuristics minimising the number of stock outs. It is stated that by selecting a correct storage and replenishment strategy, stock outs can significantly be reduced, which increases the total productivity of the warehouse. Besides storage assignment strategies, picker routing is also influenced as products can be unavailable when arriving at a location. Constraints can be included when creating routes to check whether or not inventory is available at a location (Daniels, Rummel, and Schantz 1998; Cortés et al. 2017). Orders can be picked at multiple locations (in case of a scattered storage policy), partially picked or completely removed from the problem if inventory levels are too small (Daniels, Rummel, and Schantz 1998).

4.4.2. Obsolete inventory

Companies often upgrade their product assortment due to technological advances but keep older versions of the product in stock as a service to the customer, which leads to an excessive amount of slow-moving or obsolete inventory items (Min 2009). Analysing obsolete inventory in order picking planning problems is very scarce with only two articles (Figure 3). Min (2009) develops a warehousing decision support system for strategic warehouse expansion and several re-warehousing decisions among other rearranging inventories of fast-moving, slow-moving and obsolete products. Manzini et al. (2015) develop a MILP model to address the assignment of products to storage areas based on a life cycle picking metric (i.e., rolling measure of popularity).

4.4.3. Scattered storage

Scattered storage has been hardly investigated in academic literature as can be seen from Figure 3. Assigning fast moving products to multiple locations (i.e., using scattered storage) directly influences the nature of the storage location assignment and picker routing problem. Scattered storage imposes additional decision variables to the storage and routing models. Storage assignment is not limited to deciding on where to store an item, but also which item to store on multiple locations and where to store which quantity of an item (Anken et al. 2011; Jiang et al. 2020; Yang, Zhao, and Guo 2020). Moreover, when a pick list is created the routing problem defines not only the sequence in which locations should be visited, but also which location is visited to retrieve a product (Daniels, Rummel, and Schantz 1998). In a dynamic context (i.e., real-time order arrival), multiple locations may enhance the efficient inclusion of an order to a pick list that has already been started (Weidinger 2018; Weidinger, Boysen, and Schneider 2019). Irrespective of the pickers position within the warehouse, items of a requested product will be closer (Weidinger and Boysen 2018). Although pick tours can be shortened to a large extent in scattered storage, the continuously changing storage assignment is often very confusing for order pickers. The time to search and retrieve items may increase compared to other strategies (e.g., dedicated storage in which order pickers quickly memorise fixed product locations). Batt and Gallino (2019) state that this negative effect of searching decreases with picker experience.

5. Implications for research and practice

Results of the literature show the importance of accounting for practical factors in planning problems in order to optimise and manage order picking operations. Figure 4 highlights the relevant combinations of practical factors and planning problems and the extent to which the combinations of practical factors and planning problems have been investigated in academic literature for all relevant combinations of planning problems and practical factors. Based on this figure, this section discusses the practical implications of the research results for warehouse managers, but also emphasizes the need for researchers to account for perspectives of practitioners in future scientific research. Only a small fraction of academic literature on order picking planning considers the practical factors here described. The majority of literature still holds on to unrealistic assumptions such as wide pick aisles with traffic in all directions, the possibility to overtake pickers in every aisle, ignoring vertical lifting during picking, assuming a single order picker (or an infinite number of pickers) in the system or using travel distance as a single performance measure. Most of the practical factors significantly change the problem structure and forthcoming results. Ignoring the identified factors, or making unrealistic assumptions about them, leads to unrealistic or infeasible solutions in practice or results in biased recommendations for managerial decision making when the order picking system is subject to one or more of the practical factors.

Strategic decision making such as rack configuration, technical equipment and depot location influence the tactical and operational planning problems such as zoning, storage assignment, batching, routing and job assignment and these are at their turn influenced by different practical factors. As can be deduced from figure 4, strategic decisions are mainly influenced by practical factors of the system factors category. The footprint of a storage system (the number of aisles and aisle length and width) strongly impacts horizontal travel time. If warehouse management opts for wide aisles, this means that there is less space for storing products and travel distance typically increases. However, pickers are often allowed to overtake in these aisles, reducing wait times induced by picker blocking. On the other hand opting for narrow aisles, storage capacity increases and pickers travel less as both sides can be picked from the middle of the aisle. However, picker blocking in these systems increases wait times and significantly impacts total system performance. The number of levels in a storage system impact vertical travel time. Slow lifting impacts the routing problem but also makes storage assignment more complex, requiring an assignment among multiple levels. The impact of high-level storage is negligible when the highest locations are reserved for replenishment and picking is performed at ground floor. Not only picker blocking should be considered while configuring storage racks, but also imposed safety regulations (e.g., traffic rules as a result of narrow aisles). Furthermore, human factors also influence strategic decisions. For example, management should carefully consider which technical equipment suits the company best as not all devices are equally accepted by pickers as pick support. For example, the field study of De Vries, De Koster, and Stam (2016b) proves that pick-by-voice performs better than RF-terminal picking and that neuroticism, extraversion, conscientiousness and the age of the picker play a significant role in predicting picking performance with voice and RF-terminals.

Tactical decisions are influenced by multiple practical factors. Figure 4 shows that within zoning (i.e., zone location, zone assignment and zone picking), the influence of picker blocking, resource constraints and multiple human factors are dominant. Zoning is often introduced in warehousing so that pickers traverse smaller areas, promoting learning for order pickers as it is easier to get familiar with the products. With the

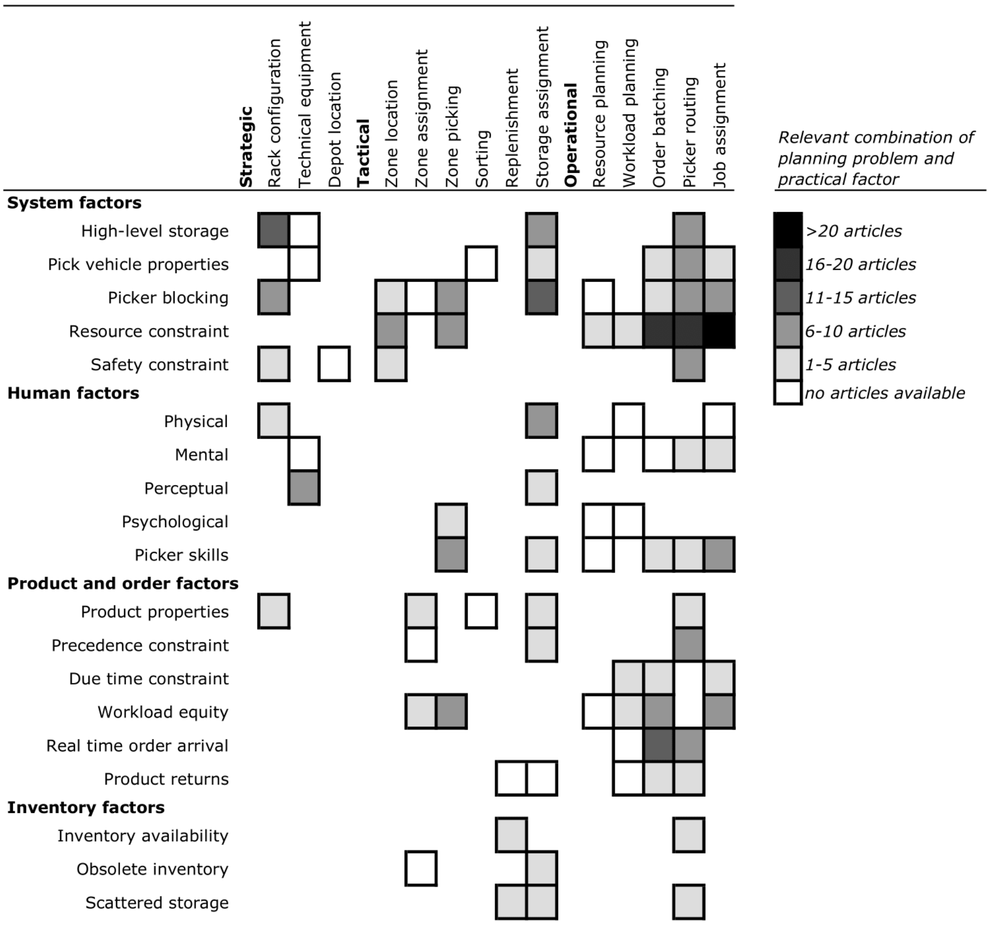

Figure 4. Relevant combinations of practical factors and planning problems.

implementation of zoning, pickers can only travel in a limited number of pick aisles each pick tour and therefore wait times due to picker blocking shrink (Van Gils et al. 2019b). However, this statement depends on how items are assigned to zones. Zones that store fast moving products in order to reduce travel times may result in increased picker blocking in front of specific storage locations or even block the entire aisle if pickers cannot overtake. Therefore, in practice, a limited number of pickers is typically allowed in each zone and, to increase safety, traffic rules are imposed, which should be accounted for by research in modelling. On the other hand, managers should not be blind sighted by the reduction in travel time as picker blocking, safety and resource constraints can significantly limit the positive results of zoning. Besides zoning, another tactical factor that is highly influenced by practical factors is storage assignment. The same effects should be considered here. Storage is reassigned occasionally to increase productivity. However, if not accounted for picker blocking, pick vehicle properties (i.e., not all trucks can reach all locations) or human factors, the benefits of a reassignment can be undone. For example, the gains in productivity of a storage reassignment depend on the ratio of experienced order pickers to temporary workers. When there are more experienced order pickers, loss in order picking time after storage reassignment will be high, caused by forgetting. More orders need to be processed in the new situation to break even compared to the previous policy (i.e., pickers increase performance by processing orders) (Grosse, Glock, and Jaber 2013). Furthermore, storage assignment methods need to account for ergonomic goals, as an ergonomically favourable storage assignment can unburden workers during their pick activities (Petersen, Siu, and Heiser 2005).

Operational decision making in warehouses becomes increasingly complex as warehouses strive for fast and accurate deliveries but also have to take into account the health of their workers as order picking is a demanding job. From figure 4 it can be deduced that batching and routing decisions are heavily influenced by several system factors, as described before in the paragraph on strategic decisions. Moreover, figure 4 also shows that operational decisions such as batching and routing are influenced by varying product and order factors. Batches should be created so that capacity restrictions of the pick cart are not violated and routes may not violate any precedence constraints, preventing products from getting damaged. Workload should be evenly spread during the day to prevent stress for order pickers (Vanheusden et al. 2020b). Workers can benefit from a task assignment that is better suited for their own skills and capabilities, thereby increasing system performance (Matusiak, De Koster, and Saarinen 2017). Warehouse managers should be aware that more efficiency can be reached by not only checking for the qualifications of pickers (e.g., reach truck certificate) to assign them to a job, differences among pickers with the same qualifications also play an important role. Management should weigh up the benefits of optimal operational policies, which are rather complex for workers to understand against more intuitive, heuristic approaches for managing daily order picking operations (Glock et al. 2017).

6. Research opportunities

Findings from academic research are not always implemented in practice. Warehouse managers rather use simple policies that are easy to understand for all warehouse employees, but these policies result in solutions that are far from optimal. Researchers on the other hand, often fail to account for perspectives of practitioners, leaving a lot of potential for increasing the practical applicability of research on planning order picking operations. In this research, we identify, classify and analyse practical factors that have an impact on strategic, tactical and operational planning problems for order picking. Figure 4 shows that literature accounting for practical factors in the relevant order picking planning problems is scarce and for a large number of categories even not existing. In general, more research is needed to extent the current knowledge and to generalise and validate existing studies.

In research on system factors, most attention is paid to resource constraints, followed by picker blocking. However, more extensive research is needed on how to plan and manage resources in order picking. Second, future research should focus on identifying all possible components that result in congestion (e.g., storage rack blocking) and determine which components are essential in warehouse settings with varying order picking policies. Third, there remains a strong need to investigate warehouse safety, both to reduce accidents by proposing new safety regulations (e.g., traffic rules) and to increase efficiency by accounting for safety constraints in existing planning problems. A final research opportunity in the context of system factors, more specifically pick vehicle properties, is to abandon the assumption of a linear relation between travel distance and travel time.

Despite the important role of humans in manual order picking, research on human factors is still very limited. Accounting for physical aspects in storage assignment often results in heavily occupied (i.e., frequently visited) storage locations that have a favoured ergonomically position. This results in a substantial increase of picks on these locations and therefore the effect of picker blocking on these ergonomically favoured storage positions is an interesting track for future research. Next, as the majority of studies integrating picker skills use very specific warehouse circumstances, more research is needed for different warehouse circumstances and layouts to be able to generalise results. Only few articles consider mental, perceptual and psychosocial factors in planning order picking operations. Investigating different organizational measures that could foster learning in order picking systems can lead to interesting opportunities. Finally, research on augmented reality in order picking is still significantly behind in comparison to research in other industries (e.g., retail).

Varying product and order properties result in varying retrieval times at storage locations. In contrast to strongly varying product properties, the negative consequences of highly similar products (e.g., pick errors, increased search times) is unexplored in academic planning models. Furthermore, product returns received too little attention in literature, giving opportunities for future research. Moreover, future research should provide decision support tools that schedule customer orders with the aim of workload equity over time: controlling the order arrival or rescheduling truck departures minimise workload peaks in particular time periods. Finally, research typically assumes that all orders are known at the beginning of the planning period and all order due times are at the end of the planning period which is in contrast with current market conditions. These dynamic effects are essential to account for when planning order picking operations.

Research on inventory factors deserves more thorough research for inventory availability, obsolete inventory and scattered storage. More research is needed on so called “life cycle picking” in order to generalise obtained results and in order to identify general guidelines that are useful for practitioners in terms of inventory availability and obsolete inventory. Studies on scattered storage often simplify or ignore other practical factor that can have a major influence on the research results. Therfore, attention should be paid to other practical factors, influencing research results for scattered storage systems.

Finally, it should be noted that planning problems may be influenced by multiple practical factors. The effect practical factors have on order picker planning can, at their turn, be influenced by interdependencies among different planning problems. In general, academic literature should evolve to more integrated solution algorithms that consider multiple practical factors such as the works of Cortés et al. (2017) or Van Gils et al. (2019b). This would lead to more realistic research results. An important condition to build more realistic models is the availability of real data. Furthermore, this research can support future research on practical factors in automated systems, as a lot of the identified practical factors also influence order picking planning in these robotised systems (e.g., workload balancing, resource constraints, due time constraints).

Data Availability Statement

All data is included as online attachment to the paper.

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