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The Impact of Writing Direction on Order-Picking Performance: Evidence on Diversity and Efficiency in Operations Management

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Abstract

Language system diversity is a source of individual differences. Research on human cognition has established that writing direction influences non-linguistic mental schemata such as spatial orientation. However, there is little empirical evidence of its impact on task performance. We examine whether task performance in manual order-picking is higher when the in-aisle travel direction follows the writing direction of order pickers. We conducted this study in cooperation with a German brick-and-mortar grocery retailer, allowing us to employ a unique real-world data set comprising 3,200,534 storage-location visits by 113 order pickers, 61 of whom had a left-to-right and 52 a right-to-left writing direction. Our statistical analyses suggest that order-picking task performance improves when the in-aisle travel direction follows individual writing direction. This creates a path to diversity-inspired operations management that treats efficiency and the diversity and inclusion of human workers as equally important for optimization.

Keywords

Language diversity, order-picking, writing direction, diversity in operations management

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1 Introduction

Matching operating system policies to individual worker characteristics is a central avenue through which firms can improve operational performance (Bendoly et al., 2010; Donohue et al., 2020). The behavioral operations management (BOM) literature establishes that individual picker characteristics, such as motivation (de Vries et al., 2016a), personality (de Vries et al., 2016b), experience (Grosse and Glock, 2015), and learning speed (Loske, 2022), are sources of individual differences impacting operational performance. Recent studies identify the potential for improvements in manual order-picking when, for example, batch assignment takes picker skills (Matusiak et al., 2017) or prior picker experience into account (Batt and Gallino, 2019) and when prior human deviations are incorporated into algorithmic prescriptions (Sun et al., 2022). Although warehouses typically host diverse workforces, the BOM literature on manual order-picking systems pays little attention to diversity, equity, and inclusion (DEI) factors as a source of individual differences that might impact operational performance.

Given that DEI-related factors are integrated into the United Nations Sustainable Development Goals, it is surprising that operations management (OM) scholars have yet to investigate the performance implications of DEI efforts.

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The lack of attention to DEI in the literature is also problematic—diversity research suggests that language-based diversity may impact other non-linguistic perceptual schemata such as spatial orientation (Bergen and Chan Lau, 2012; Román et al., 2013). English speakers (who learn a left-to-right writing direction) use a spatialized mental number line oriented from left to right. In this perceptual schemata, small numbers are associated with the left side of a space, and larger numbers are associated with the right side (Bächtold et al., 1998; Shaki et al., 2009).

However, operating system policies may require order pickers to navigate through the warehouse and travel in different directions, for example, from right to left in an S-shaped route. In such circumstances, the interaction of operating system policies and DEI-related individual differences may have performance implications. We address this gap by answering the following research question: Is task performance in manual order-picking higher when in-aisle travel directions follow the writing direction of order pickers?

We employ empirical field data extracted from a picker-to-parts order-picking system to investigate this question. The archival data are accessed through a partnership with a nationwide brick-and-mortar retailer operating twenty warehouses in Germany. We obtain information about writing direction as primary data through short surveys of order pickers on completion of a batch picking. The data set covers the period from March 2022 to June 2022 and includes 3,200,534 storage location visits. We select 113 participants from among the 238 order pickers employed in the warehouse. The data identify the writing direction of participants' first written language (the language in which they first learned to read and write) as left to right for 61 participants and as right to left for 52 participants.

This article is intended to strengthen the dialog between DEI and OM, with a view to enhancing our understanding of how these interact. We offer a first-of-its-kind empirical proof of the hypothesis that the writing direction of the first written language of an order picker substantially influences their order-picking performance. This may inspire other efforts to connect human-in-the-system diversity with operational performance. Such empirically based insights would allow operations managers to design and implement inclusive and efficient operations systems that consider individual-level and diversity-driven heterogeneity.

The remainder of the article is structured as follows. In Section 2, we present related literature. In Section 3, we describe our empirical strategy, and in Section 4, we introduce our statistical model. After presenting our empirical results in Section 5, we discuss the theoretical and managerial implications of language-based diversity in Section 6.

2 Related Literature

With over 7,000 recognized languages worldwide, linguistic differences are a source of considerable individual human diversity (Bromham et al., 2022). Across the world, communities have developed unique writing and reading systems that have shaped the way that humans perceive and interact with their environment (Chan and Bergen, 2005; Fitch, 2010). Given that writing and reading are among the most frequent and spatially systematic ways humans interact with their environments, learning a particular language entails mastery of mental routines in the direction of writing systems (Maass et al., 2007; Bergen and Chan Lau, 2012).

These mental routines vary depending on the direction in which the text is written (Gevers et al., 2003; Faghihi et al., 2019). While Latin writing systems are directed from left to right and top to bottom, this is by no means the only option; written Arabic and Hebrew runs from right to left and then top to bottom, and, Chinese and Vietnamese writing goes from top to bottom and then right to left (Suitner and Giacomantonio, 2012). This suggests that humans who differ in terms of their writing direction also differ in how they think and interact differently in writing and reading tasks. There is evidence that the direction of writing also influences mental schemata, such as spatial orientation (Chan and Bergen, 2005).

The literature reflects a general agreement that human cognition organizes the world into non-arbitrary semantic concepts and that how humans order mental categories has a major impact on how they perceive their environment (Rosch, 1973; Gärdenfors, 2020). According to the theory of spreading activation in semantic memory networks, initially proposed by Collins and Loftus (1975), abstracting the environment in semantic concepts (e.g., discriminating between storage location 01-0020 and 01-0048) and into different cognitive categories (e.g., the left side of the aisle) by means of various neural networks is a basic feature of the cognitive system by which humans simplify the environments in which they operate (Gärdenfors, 2020). For simple discrimination tasks, mental categories are connected through links representing their weighted relationship (Dobel et al., 2007). For example, Huttenlocher (1968) refer to the three-term series problem, which demonstrates one principle of transitivity: Knowing that $x > y$ and $y > z$, one can conclude that $x > z$. In a spatial representation of this relationship, one may think of a chain as a horizontal sequence in the mental space, for example, *x-y-z* (von Hecker and Klauer, 2021); this chain need not run from left to right.

Such patterns suggest some systematic relationships between writing direction and mental schemata beyond the tasks of writing and reading (Maass et al., 2016). As evidence, various studies show that writing direction impacts spatial mental number lines, conceptualized as the spatial–numerical association of response codes (SNARC) effect. In this regard, Dehaene et al. (1993) proposed that the mental representation of numerical magnitude is related to the left–right axis for humans with a left-to-right writing direction. Therefore, large numbers elicit faster rightward task responses, and small numbers elicit faster leftward task responses (Ninaus et al., 2017). Shaki et al. (2009) find empirical support for a reversed

SNARC effect for Arabic speakers with a right-to-left writing direction. Gevers et al. (2003) also find a SNARC-like effect for nonnumerical ordinal information. This suggests that writing direction is, in general, associated with the mental schemata of sequences (Zebian, 2005).

Mental schemata of sequences are structures relevant for spatial orientation, that is, the ability of humans to understand the environment in relation to their own bodies (egocentric orientation) and in relation to external points of reference (allocentric orientation) (Byrne et al., 2007). Spatial mental models include those that help us understand the layout of the environment and our position therein and those that allow us to navigate and move through that environment (Santoro et al., 2021). There is growing empirical evidence that writing direction affects mental spatial representations (Zhou et al., 2019). Tversky et al. (1991) proposed that the directionality of represented relations is affected by writing direction, with left-to-right dominant for English speakers and right-to-left for Arabic speakers. Kazandjian et al. (2009) go on to show that writing direction and egocentric reference in spatial orientation are closely related. Bergen and Chan Lau (2012) extended this understanding using a task in which participants had to arrange a set of three pictures in a sequence from the earliest to the latest on a cardboard tray. Relatedly, Mishra et al. (2015) demonstrated a left-to-right bias in an orientation task when crossing streets in the absence of barriers or walk signals. Together, this line of research reflects the idea that writing directions affects our spatial representations of arbitrary sequences of events.

However, there is also empirical evidence that the SNARC and reverse-SNARC effects do not exclusively prime the mental representation of sequences. After replicating the SNARC effect for movement tasks, Bächtold et al. (1998) find that the number scale (from left to right) cannot be the decisive factor in the observed interaction between number size representation and hand movement. Román et al. (2013) challenged the standard view that writing direction impacts spatial mental number lines. The authors argue that habitual reading in reverse directions might lead to weaker, or even reversed, lateral spatial biases. In line with these arguments, Lopiccolo and Chang (2021) proposed that cultural factors weaken but do not reverse the spatial biases caused by writing direction. In addition, Masson et al. (2020) find that the SNARC effect is not replicable for their participants and call for current models to be reconsidered. Bender et al. (2018) suggested that writing direction alone cannot explain individual differences in spatial mental models and that including more cultural characteristics may improve predictions of performance in movement tasks.

Navigation is an essential element of movement tasks in any environment and comprises two inherently connected elements: wayfinding and travel (Jul and Furnas, 1997). Wayfinding refers to the cognitive element of navigation and is grounded in spatial knowledge. The mental representation of one's spatial knowledge of an environment constitutes a cognitive map in human memory (Darken and Peterson, 2014). This map is the basis for tactical and strategic guides for travel. Traveling is the motoric element of navigation and involves active travel, "getting from here to there," and maneuvering (a subset of traveling including small adjustments such as the reorientation of perspective when rotating along the vertical body axis or sidestepping (Bowman et al., 1997)). Wayfinding and travel are not serial events but enmeshed in the context (Suchman, 1987); observable navigation performance also depend on environmental characteristics and individual human differences. Jul and Furnas (1997) proposed a model of navigation that captures these aspects of navigation for movement tasks. Figure 1 depicts the model of navigation adapted from Darken and Peterson (2014).

Environmental characteristics are likely to define the navigation problem. Gärling et al. (1986b) identified three environmental characteristics relevant to navigation: the degree of differentiation, the degree of visual access, and the complexity of the spatial layout. The degree of differentiation is the degree to which parts of an environment look the same or different, which affects the ability of humans to wayfind elements and travel paths (connecting elements) or nodes (intersections and junctions among routes). The degree of visual access refers to the extent to which parts of the environment are visible from other parts. Wayfinding and traveling to distant locations are enhanced when there are vantage points from which other parts of the environment or targets in that environment are visible. Spatial layout complexity is related to the size of the environment, the number of elements therein, possible routes through the environment, and intersections and junctions among routes (Evans et al., 1984). According to the classification by Gärling et al. (1986a), a low degree of differentiation and visual access and a highly complex spatial layout reflect a high level of navigational problems and a potentially high effect of individual human differences in navigation performance.

Typically, warehouse environments present many such navigational problems as order pickers move from one location to another. Order-picking includes the task of finding an exact predefined location in a complex environment by, for example, following a route from the left to the right side of the aisle. These route-following tasks require spatial comprehension and the ability to perceive, understand, remember, and recall solutions to navigation problems for future use. However, a range of elements might depend on the order picker's writing direction, for example, individual differences in the time required for wayfinding, egocentric spatial orientation to understand the environment in relation to one's own body, allocentric orientation to understand the relation to external reference points, active traveling, maneuvering, or strategy collection in route-following tasks. We thus investigate whether task performance in manual picker-to-parts order-picking is higher when the in-aisle travel direction follows the order pickers' writing direction. We identify a set of possible

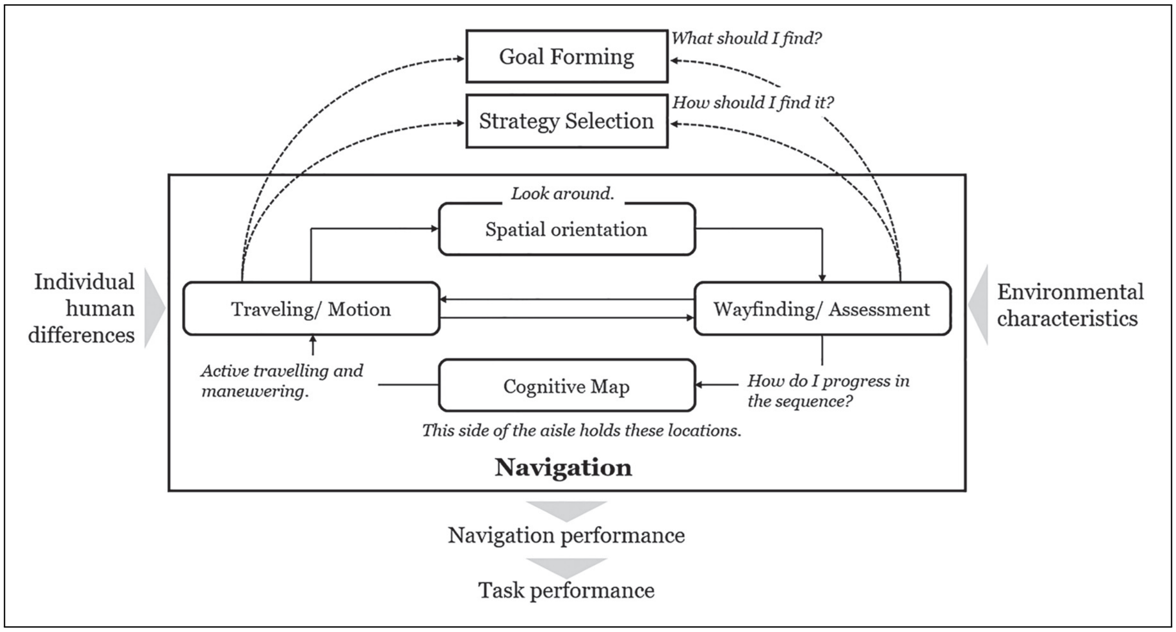

Figure 1. Model of navigation adapted from Darken and Peterson (2014).

mechanisms through which diversity in writing direction may lead to differences in task performance:

- Cognitive map: Humans construct cognitive maps to navigate warehouse environments based on their spatial knowledge. Writing direction may influence the way these are constructed and interpreted, which can, in turn, lead to differences in the time required for wayfinding, thereby impacting order-picking task performance.
- Spatial orientation: Spatial orientation, both egocentric and allocentric, is crucial for understanding and navigating warehouse environments. An individual's writing direction might influence their spatial orientation, as it affects their habitual spatial representations. Disparities in spatial orientation can lead to differences in travel speed when moving on paths or through intersections and junctions among routes, impacting order-picking performance.
- Strategy selection: Navigating aisles requires understanding sequences within the spatial layout, especially when the pick lists are fixed in sequence. Writing direction could shape the mental schemata of sequences, affecting how individuals perceive and navigate a sequence of elements (in this case, storage locations). When navigating sequences, individuals may, depending on their writing direction, take varying paths with varying travel distances, impacting their order-picking performance.
- Environmental characteristics: Environmental differentiation, visual access, and spatial-layout complexity might be perceived and interpreted differently based on one's writing direction. Hence, an order picker with a right-to-left writing direction may perceive right-to-left traveling as an easier navigation problem than left-to-right traveling. Individuals with different writing directions may exhibit varying paths with varying travel distances when navigating sequences, which might impact their order-picking performance.

We examine whether order-picking performance improves when the in-aisle travel direction aligns with the order pickers' writing direction and describe our empirical setting in Section 3.

3 Empirical Setting and Data

3.1 Data Sources and Warehouse Layout

The entire data set was collected in co-operation with a nationwide brick-and-mortar grocery retailer operating twenty warehouses for cooled and non-cooled products and nonperishable goods in Germany. At the time of data collection (between March 2022 and June 2022), this retailer specialized as a full-range grocery retailer and operated about 3,700 stores at the time of data collection; the data cover 3,200,534 storage-location visits. The warehouse selected for this study stored non-cooled perishable products organized in several independent areas for products with different required storage temperatures. During our observation period, the 42,000-m^2 facility processed an average of 130,000 stock-keeping units per day and stored between 5,787 and 5,937 products in an area for non-cooled perishable products. Zones are differentiated based on the groups to which products are assigned. Pickers travel with motorized industrial trucks through the various aisles using an S-shaped routing system.

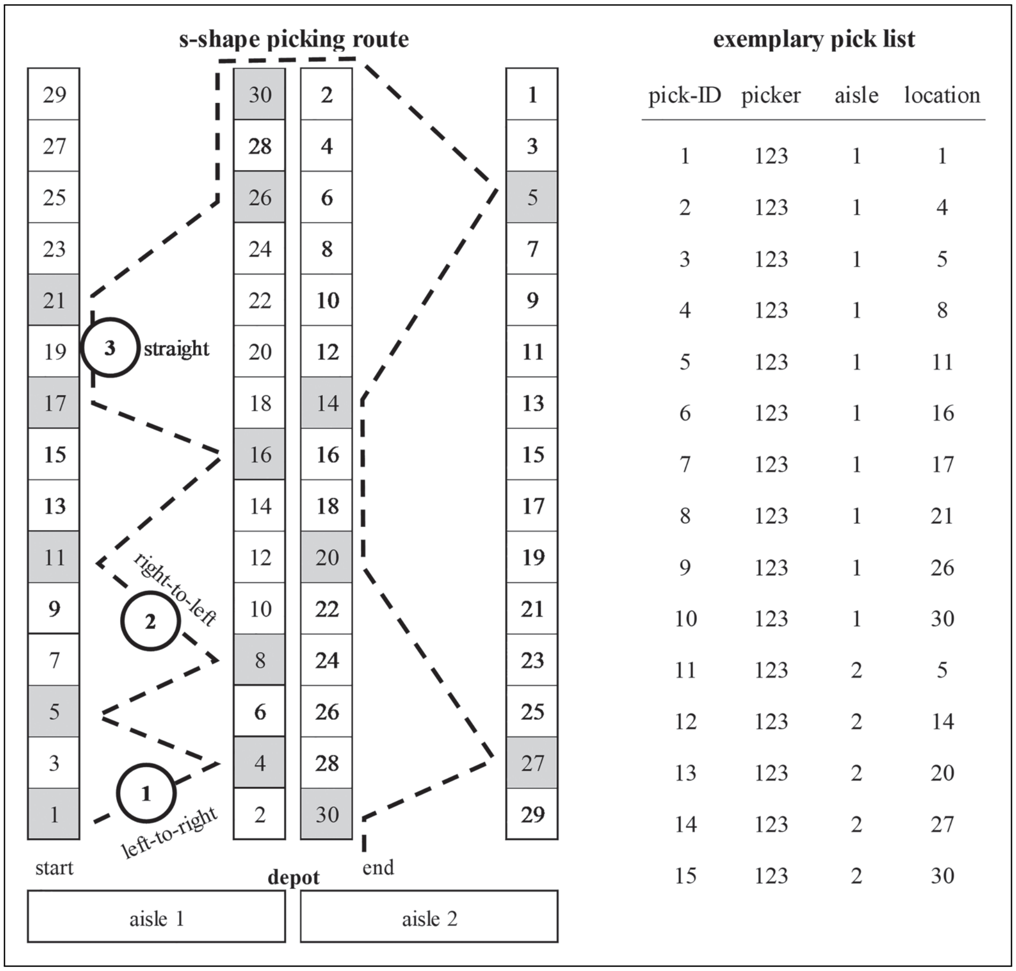

Figure 2. Picker travel in the studied company's s-shaped routing method.

The warehouse considered here has a rectangular layout for low-level picker-to-parts order-picking, with vertical picking aisles arranged in parallel. The horizontal cross aisles do not contain any storage locations but enable order pickers to travel from one aisle to another. There was one depot positioned at the center of each front cross aisle. In applying the S-shape routing method to the entire warehouse, a picking aisle must be traversed in one direction and, once the area is entered, must be completed. The left side of Figure 2 depicts a sample S-shaped route and demonstrates that spatial orientation plays a pivotal role in order-picking.

As indicated by the encircled digits, order pickers are required to constantly switch from left to right (1) and right to left (2) when moving through the aisles. The pickers are provided a pick list containing a fixed sequence of storage locations to visit, as depicted on the right side of Figure 2.

3.2 Participants

Our starting point in the process of gathering empirical data is an archival data set containing order-picking performance data from the warehouse management system provided by our research partner. This data set includes picking data for 238 order pickers employed during the sample period. After an initial screening of the data set, we approached our partner to acquire additional order-picker data, such as age and writing direction. In close co-operation with the company, we surveyed order pickers at the warehouse on a day on which a majority were present; 183 order pickers were present on the day of the survey, and 55 (23.11%) were absent due to vacation or sickness. Given the limited time for our survey (we were restricted to one day), it was not possible to survey all 183 order pickers. Some order pickers declined to participate because they felt the survey might be too time-consuming, were concerned about the confidentiality of their personal information, or were uncomfortable sharing specific personal details on the job.

We aim to obtain a balanced sample that adequately matches the general population of order pickers and, therefore, positioned ourselves at the central depot approached by order pickers at the end of a batch. We paid particular attention to gender in the sampling process, as we wanted to avoid a sample heavily dominated by men, which would make it difficult to generalize the findings to pickers who are women. Our final sample comprises 113 order pickers (24 women and 89 men), adequately reflecting the gender distribution in the warehouse picker population. We mitigate concerns related to selection bias by comparing the average pick travel time of the surveyed pickers (113) to those of non-surveyed pickers (70), which did not reveal any systematic differences between the groups.

We distinguish between participants' native language (that they grew up with) and their first written language, the language in which they first learned to read and write. We use the latter to define their writing direction. Of the 113 participants, 61 learned a left-to-right writing direction with their first written language (15 women, 46 men). Of these, 21 are left-handed, and the remaining 40 are right-handed and aged between 18 and 48 (mean 31.6 years, standard deviation 7.27 years). Another 52 participants learned to write from right to left in their first written language (9 women, 43 men), with 14 left-handed and 38 right-handed persons in this second group; their ages range from 21 to 54 (mean 36.4 years, standard deviation 9.72 years). All participants had, at the time of observation, been employed by the company for at least a year and had processed at least 3,000 batch lines in the observation period from March 2022 to June 2022.

3.3 Data Aggregation and Data Cleaning

We define our unit of analysis as a single storage location i visited by an order picker j when traveling through the warehouse to retrieve a given number of products from that location. The aggregation of data at the level of storage location visited for picker traveling allows us to distinguish whether an order picker had to travel on a diagonal from left to right or from right to left or if they remained on the same side when moving from i to $i + 1$.

We place restrictions on the data we use since we are interested in the impact of writing system diversity on order-picking performance under typical conditions. We start with a data set comprising 3,386,904 location visit observations from March 2022 to June 2022. We check the dependent variable, pick travel time, and decide that a maximum of 11,782.00 seconds (for one storage location visit) is unlikely to reflect a realistic time for the process under investigation; this observation is perhaps the result of workers forgetting to manually log off the system. We thus exclude all values above the 95th percentile (60 seconds) and are left with 3,200,534 observations. We provide detailed descriptive statistics for all variables in Appendix 1. The final data set includes N = 3,200,534 storage location visits by 113 order pickers.

4 Statistical Model and Variables

Our empirical analysis focuses on estimating how the effect of picker diversity (writing direction as our independent variable of interest) on order-picking performance (dependent variable) varies depending on the in-aisle travel direction (moderator). Given the longitudinal nature of our study, we measure order-picking performance for each order picker repeatedly. Given that repeated measurement of individuals would violate the assumption of independence of observations in standard linear regression models (observation-level errors ϵ are assumed to be independent), we propose a mixed-effects model with random slopes. Mixed-effects models allow individual order pickers to be measured more than once without artificially inflating our estimates. Since our statistical analysis in Section 5 presents variations of a single statistical model, we began by describing the base model, including the dependent, independent, and control variables and the between-subject variance.

4.1 Dependent Variable

Our dependent variable, order-picking performance, is measured as pick travel time (mean = 19.60; sd = 12.01); this is defined as the time elapsed in seconds between storage location i-1 and i by picker j in aisle k, including the time to pick products from storage location i. The clock starts when the order picker enters the check digit of storage location i-1 on a personal digital assistant mounted on the industrial truck. The device maintains a constant wireless connection with the warehouse management system, which documents relevant time stamps. After traveling to storage location i, the clock stops when the order picker enters the check digit of storage location i to pick the required number of products. Pick travel time is measured as a continuous metric variable.

4.2 Between-Subject Variance

Next, we test whether we need to account for between-subject variance by incorporating random slopes. Random slopes address the dependence between observations by clustering observation-level data from the same high-level subjects, for example, participants (order pickers) or other subjects (picking aisles) (Antonakis et al., 2021). Random effects account for any between-subject variance that might arise from order-picker heterogeneity (Matusiak et al., 2017).

We test whether we need to include random effects by calculating the intraclass correlation coefficient (ICC) for three separate no-predictor models. We test whether within- and between-subject variance exists for (a) order pickers, (b) aisles, and (c) the interaction of order pickers and aisles. The ICC values of the no-predictor models can be interpreted as the total amount of variance in the dependent variable pick travel time originating from picker- or aisle-related variation. These variations are attributed to the between-subject variation (between-picker, between-aisle, and between-picker-aisle interaction) rather than within-subject variation over time. Higher values also indicate a nontrivial degree of observation non-independence, making traditional regression approaches inappropriate (Bell et al., 2019).

The ICC value for pick travel time is 0.047 for order pickers, 0.045 for aisles, and 0.073 for the order picker—aisle interaction, indicating that between 4.5% and 7.3% of the variance in pick travel time is attributable to between-subject variability; the remainder is explained by within-subject variability over time. The ICC values suggest that pick travel time differs between order picker j, aisles k, and across interactions. Estimating more complex models with hierarchies and temporal change is thus warranted.

We thus allow order picker j to vary as a random main intercept α_j to account for order picker heterogeneity. Furthermore, we allow aisle k to vary as a random intercept δ_j to take into account aisles-based differences (e.g., products with specific characteristics stored in specific aisles). Finally, $(\alpha\delta)_{jk}$ denotes the random interaction term between picker j and aisle k. Note that $(\alpha\delta)_{jk}$ is treated as a crossed random effect and not as a nested random effect because there is no fixed assignment of order picker j to aisle k. For a detailed introduction on mixed-effects modeling with crossed random effects for subjects, see Baayen et al. (2008).

4.3 Independent Variable

Our main independent variables of interest are the interactions between two dummy variables, namely, in-aisle travel direction and writing direction. Writing direction is a binary variable ($k = 2$) reflecting the left-to-right or right-to-left writing direction of order pickers. We dummy-coded left-to-right writing direction as follows:

$$LTRwrite_i = \begin{cases} 1, & \text{if left-to-right writing direction is observed for the order picker} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

And right-to-left writing direction as:

$$RTLwrite_i = \begin{cases} 1, & \text{if right-to-left writing direction is observed for the order picker} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

We also capture aisle travel direction as a three-stage categorical variable ($k = 3$) when order pickers travel from left to right, right to left, or in the same direction within the aisle. We denote the dummy variables as follows:

$$LTRtravel_i = \begin{cases} 1, & \text{if left-to-right travel direction is observed} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$RTLtravel_i = \begin{cases} 1, & \text{if right-to-left travel direction is observed} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$sametravel_i = \begin{cases} 1, & \text{if same travel direction is observed} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Our primary interest is in how the effect of writing direction on pick travel time varies depending on the in-aisle travel direction, mathematically expressed as the interaction term of writing direction × in-aisle travel direction. Therefore, we first integrate the interaction terms of left-to-right writing direction × left-to-right travel direction and left-to-right writing direction × right-to-left travel direction, which is compared to same-direction travel when the picker's writing direction is from left to right. Note that we do not include same-direction travel to avoid the dummy variable trap while the effect is absorbed in the intercept. The same logic applies to right-to-left writing direction × left-to-right travel direction and right-to-left writing direction × right-to-left travel direction.

4.4 Control Variables

First, we control for travel distance, capturing the distance between storage location $i-1$ and storage location i. Prior studies on order-picking confirm that travel distance has a major impact on order-picking performance (Pan et al., 2014; Masae et al., 2020). We need to account for travel distance because it is included in our dependent variable, pick travel time.

Second, we account for product weight and volume characteristics because the OM literature firmly establishes the impact of product characteristics on order-picking performance (Wänström and Medbo, 2008; Finnsgård et al., 2011; Finnsgård and Wänström, 2013).

Third, we add the variables storage and stacking level to account for the height of location i at which products are stored and the level at which these are stacked and sorted after retrieval. Petersen et al. (2005) included height in their empirical modeling. Picking height might interact with product characteristics because a different physical effort may be required when retrieving and stacking products (Finnsgård and Wänström, 2013; Hanson and Finnsgård, 2014; Hanson et al., 2018). Finally, we control for pick density, capturing the number of products retrieved from storage location i. Batt and Gallino (2019) find that pick density has a significant impact on order-picking performance. Finally, we add ϕ, capturing time-related effects to control for month, day of the week, and hour of the day; ϵ_j is the error term.

4.5 Model Formulation

To avoid possible validity concerns, we first tested the correlation for all variables and attach a correlation table in Appendix 1. Furthermore, we calculated the variance inflation factors (VIFs) for each variable. Our model is denoted as follows:

$$\begin{aligned}
&Log(Travel_Pick_Time_{ijk}) \\
&\quad = \gamma_{00} + \alpha_{0j} + \delta_{0k} + (\alpha\delta)_{0jk} + \beta_{1j} LTRwrite_i \times LTRtravel_i \\
&\qquad + \beta_{2j} LTRwrite_i \times RTLtravel_i + \beta_{3j} RTLwrite_i \times LTRtravel_i \\
&\qquad + \beta_{4j} RTLwrite_i \times RTLtravel_i + \beta_{5j} LTRwrite_i \\
&\qquad + \beta_{6j} Travel_Distance_i + \beta_{7j} Product_Weight_i \\
&\qquad + \beta_{8j} Product_Volume_i \\
&\qquad + \beta_{9j} Storage_Level_i + \beta_{10j} Stack_Level_i \\
&\qquad + \beta_{11j} Pick_Density_i + \phi + \epsilon_{ijk} \qquad (6)
\end{aligned}$$

$$\alpha_{0j} \sim N(0, \sigma_\alpha^2) \qquad (7)$$

$$\delta_{0k} \sim N(0, \sigma_\delta^2) \qquad (8)$$

$$(\alpha\delta)_{0jk} \sim N(0, \sigma_{\alpha\delta}^2) \qquad (9)$$

5 Empirical Results

5.1 Model Free Results

To ease the interpretation of our empirical results without requiring a deep statistical background, we present the group means and standard deviations per condition as model-free evidence. We begin by examining the group means for conditions of in-aisle travel and writing direction. We include in-aisle travel from left to right, right to left, and in the same direction. For the writing direction, we create group means for left-to-right and right-to-left travel. Descriptive statistics are intended to facilitate the understanding of our results without the need to understand all conditions of our multilevel model.

Table 1 summarizes the group means for each of the 2×3 conditions. When we view our moderator in-aisle travel direction in isolation, the group means range from 19.08 (left-to-right travel direction) to 20.20 (right-to-left travel direction). The group means for the order picker's writing direction show a pick travel time of 19.45 seconds when the writing direction is right to left (0.77% difference from grand mean) and 19.72 when it is left to right (0.60% difference from grand mean).

We are interested in the interaction of the direction of writing and the direction of in-aisle travel and identify significant differences when comparing the group means in a 2×3 matrix. We find the lowest pick travel time when the writing direction of the order picker is aligned with the in-aisle travel direction, that is, 17.01 for right-to-left writing direction with right-to-left travel (in contrast to 22.42 for right-to-left travel and 19.16 for same-direction travel) as well as 16.48 for left-to-right writing direction with left-to-right travel (in contrast to 22.61 right-to-left travel and 19.71 for same-direction travel). This calls for a more detailed analysis, possibly capturing confounding effects such as product characteristics and travel distance.

Our model-free findings, which offer a preliminary overview of the relationships between pick travel time, writing direction, and in-aisle travel, suggest complex dynamics. We observe differences in group means that suggest an influence of writing direction on pick travel time, particularly when it aligns with in-aisle travel direction. However, these high-level observations do not control for numerous potential confounding factors, such as product volume and weight or travel distance. We explore the interaction between writing and travel direction by quantifying these effects, increasing our rigor by applying the previously formulated mixed-effects model.

5.2 Interaction of In-Aisle Travel Direction and Writing Direction

We use the mixed-effects model with random intercepts for order pickers, aisles, and picker—aisle interaction to examine how and to what extent the effect of writing direction on pick travel time varies with our moderator variable, in-aisle travel direction. Note that a positive coefficient is associated with a higher predicted travel time and, therefore, a negative impact on picking performance; a negative coefficient is related to a lower predicted pick travel time and a performance improvement. Table 2 summarizes the results of our mixed-effects model.

Our baseline is presented in Model (1), which includes all control variables and allows us to investigate how model fit changes with the addition of the independent variables. When we add the moderators in Model (2), we find a drop in the values for the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), indicating a better fit.

Table 1. Group means for each of the 2 × 3 conditions.

	Picker diversity effects		
	Right-to-left writing direction	Left-to-right writing direction	Group mean
Same-direction travel	19.16 (11.57)	19.71 (11.60)	19.47 (11.59)
Left-to-right travel	22.42 (13.70)	16.48 (9.78)	19.08 (12.03)
Right-to-left travel	17.01 (10.21)	22.61 (13.30)	20.20 (12.38)
Group mean	19.45 (12.06)	19.72 (11.96)	

Note: Standard deviations in parentheses; grand mean is 19.60 (12.01); N = 3,200,534 observations.

At the same time, the R^2 value, determining the proportion of variance in the dependent variable that can be explained by the independent variable, increases from 0.140 to 0.141. Given that the coefficients for the left-to-right writing direction and the left-to-right travel direction are non-significant, we can conclude that the main effects of writing and travel direction in Model (2) do not add significant explanatory value to the baseline model.

In Model (3), we incorporate dummy variables with different categories (k) holding three-stage ordinal ($k = 3$ for travel direction) and binary ($k = 2$ for writing direction) information. The default in dummy coding is to leave one reference level out and report $k - 1$ coefficient(s) interpreted in relation to the reference level. This is necessary to avoid the dummy variable trap where one variable can be predicted from the others, which leads to high multicollinearity in the model (Wooldridge, 2020). For the interactions among dummy variables, we choose to report all interactions without reference to the travel direction to avoid this trap (Buis, 2012).

We add the interaction terms for left-to-right writing direction and left-to-right travel direction, as well as for left-to-right writing direction and right-to-left travel. These coefficients are compared to the combination excluded to avoid the dummy variable trap, that is, the case of same-direction travel when the picker has a left-to-right writing direction. The estimator for the interaction of left-to-right writing direction and left-to-right travel direction is 0.176 and significant at $p < 0.01$, and the estimator for the interaction of left-to-right writing direction and right-to-left travel direction is 0.140 and significant at $p < 0.01$. Therefore, compared to the case of same-direction travel, order pickers with a left-to-right writing direction can reduce their pick travel time by 17.6% when the travel direction is aligned to their writing direction (left-to-right travel), but this time increases by 14.0% when it goes against the travel direction (right-to-left travel).

Continuing with Model (3), we also include the interaction terms for right-to-left writing direction and left-to-right travel, as well as right-to-left writing direction and right-to-left travel. These coefficients are compared to the case of same-direction travel and right-to-left writing direction, which is also not integrated to avoid the dummy variable trap. The estimator for the interaction between right-to-left writing direction and left-to-right travel is 0.161 and is significant at $p < 0.01$; the estimator for the interaction between right-to-left writing direction and right-to-left travel is -0.117 and is significant at $p < 0.01$. Therefore, compared to same-direction travel, order pickers with a right-to-left writing direction can reduce pick travel time when the direction of travel is aligned to their writing direction (right-to-left) by 11.7%, but pick travel time also increases (by 16.2%) for this writing direction when not aligned with the travel direction (right-to-left travel).

We also find that including the interaction of writing and travel direction improves model fit; the AIC is reduced from 5,606,094 to 5,470,020 when moving from Model (2) to Model (3); the BIC drops from 5,606,289 to 5,470,240. Furthermore, the R^2 value increases from 0.141 in Model (2) to 0.180 in Model (3), indicating that the interaction and independent and control variables in Model (3) can explain a greater share of variance in the dependent variable than is possible in Model (2).

As further confirmation of the structural validity of our results, we conduct a robustness check using Model (4) and replace the random effect for picker α_{0j} with a fixed effect, dropping the random interaction effect of pickers and aisles $(\alpha\delta)_{0jk}$, and keeping the random aisle effect δ_{0k}. Model (4) thus includes identical interaction terms but with time- and picker-fixed effects. A comparison of the results for Models (3) and (4) shows that the model fit is reduced in the latter case; this is indicated by the increased AIC, BIC, and R^2 values. At the same time, all estimates for the four writing-travel-direction interaction terms remain consistent in terms of the direction and magnitude of effects.

6 Discussion and Conclusion

This study examines the question of whether task performance in manual order-picking is higher when the direction of in-aisle travel and order pickers' writing direction match. We take an exploratory research approach employing a unique real-world data set that includes 3,200,534 storage location visits by 113 order pickers and find that task performance is highest when operating system policies (in-aisle travel direction) and worker diversity factors (writing direction) are aligned. Our empirical results support broadening diversity efforts within the OM domain.

Our exploratory approach makes a contribution to the literature on writing direction on a theoretical level and adds evidence that a writing-direction bias can impact the performance of tasks involving spatial orientation. Our study also

Table 2. Results on picker diversity and travel direction interaction.

	Dependent variable: Log(Travel_Pick_Time)			
	Baseline Model (1)	Baseline + IVs Model (2)	Baseline + Interac. Model (3)	Robustness Model (4)
Picker Diversity and Travel Direction Interaction				
Left_to_Right_Writing_Direction × Left_to_Right_Travel			-0.176^{***} (0.001)	-0.176^{***} (0.001)
Left_to_Right_Writing_Direction × Right_to_Left_Travel			0.140^{***} (0.001)	0.142^{***} (0.001)
Right_to_Left_Writing_Direction × Left_to_Right_Travel			0.162^{***} (0.001)	0.161^{***} (0.001)
Right_to_Left_Writing_Direction × Right_to_Left_Travel			-0.117^{***} (0.001)	-0.118^{***} (0.001)
Moderators				
Left_to_Right_Travel		−0.001 (0.0005)		
Right_to_Left_Travel		-0.029^{***} (0.0005)		
Left_to_Right_Writing_Direction		−0.001 (0.011)	0.016 (0.022)	0.115^{***} (0.002)
Control Variables				
Distance	0.003^{***} (0.00001)	0.003^{***} (0.00001)	0.003^{***} (0.00001)	0.003^{***} (0.00001)
Product_Weight	0.008^{***} (0.0001)	0.008^{***} (0.0001)	0.008^{***} (0.0001)	0.008^{***} (0.0001)
Product_Volume	0.003^{***} (0.0001)	0.003^{***} (0.0001)	0.003^{***} (0.0001)	0.003^{***} (0.0001)
Storage_Level	0.010^{***} (0.001)	0.010^{***} (0.001)	0.010^{***} (0.001)	0.009^{***} (0.001)
Stack_Level	0.001^{***} (0.00001)	-0.001^{***} (0.00001)	-0.001^{***} (0.00001)	-0.001^{***} (0.00001)
Pick_Density	0.009^{***} (0.0001)	0.009^{***} (0.0001)	0.009^{***} (0.0001)	0.009^{***} (0.0001)
Intercept and Effects				
Intercept	2.657^{***} (0.226)	2.698^{***} (0.226)	3.793^{***} (0.222)	2.471^{***} (0.026)
Time	Fixed effect	Fixed effect	Fixed effect	Fixed effect
Pickers	Random effect	Random effect	Random effect	Fixed effect
Aisles	Random effect	Random effect	Random effect	Random effect
Variance components				
Within-picker variance (σ^2)	0.34	0.34	0.32	0.34
Intercept variance τ for α_{0j}	0.01	0.01	0.01	
Intercept variance τ for δ_{0k}	0.01	0.01	0.01	0.03
Intercept variance τ for $(\alpha\delta)_{0jk}$	0.02	0.02	0.02	
ICC	0.11	0.11	0.12	0.07
Additional information				
Observations	3,200,534	3,200,534	3,200,534	3,200,534
Aisles	41	41	41	41
Order Pickers	113	113	113	113
AIC	5,611,162	5,606,094	5,470,020	5,603,438
BIC	5,611,318	5,606,289	5,470,240	5,603,645
R^2	0.140	0.141	0.180	0.143

Note: Coefficients are reported with robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Model (4) tests two-way fixed effects for individuals and time with a random effect for aisles. Therefore, intercept and ICC refer to this aisle random effect. IVs: independent variables; AIC: Akaike information criterion; BIC: Bayesian information criterion; ICC: intraclass correlation coefficient.

serves as a starting point for further explanatory research on the specific workings of the mechanisms linking writing direction and order-picking performance. Explanatory DEI research in OM could also juxtapose the writing-direction hypothesis with alternative explanations for left-to-right bias, such as hemispheric specialization (Kinsbourne, 1987) or the pseudo-neglect effect (Taylor and Heilman, 1980).

From a managerial perspective, aligning picker routing with DEI principles presents a rich opportunity for enhancing operational efficiency and inclusion in warehouse operations. We distinguish three possible approaches, each with its own implications. First, routes can be optimized based on the writing direction of the majority of order pickers. While this may simplify navigation for a significant portion of the workforce, it warrants careful consideration from a DEI perspective. Aligning routing based on a majority direction might inadvertently penalize individuals with different writing directions.

Second, existing routes could be assigned to order pickers based on their writing direction. On this approach, aspects of individual diversity are acknowledged and accommodated. Third, the routing and batching algorithms could be comprehensively transformed to generate routes that best suit each individual picker, taking into account their writing direction and other relevant diversity factors. Dynamic routing could promote fairness and inclusion in operations systems and could enhance operational performance by customizing routes at the individual level.

Ouranalysis is limited by our use of secondary data. Although we can identify the order-picker travel direction using the storage-location visits documented in the warehouse management system, we did not have access to detailed primary movement data because these were not recorded. A future research path could implement sensors to track, measure, and monitor worker activities, that is, through motion tracking systems. We remain confident that our main results are robust as travel direction is determined objectively.

The generalizability of our findings is somewhat limited. The context studied here is one in which order pickers' routes are organized in an S-shape. Our findings should be generalizable to similar contexts involving a variety of travel directions and thus necessitate continuous navigation. Our results could be dependent on the extent to which travel direction varies, and the effect may weaken in settings where navigation is less of an issue, for example, routes with mostly same-direction travel.

Our work opens the door for future research on DEI in order-picking. This study is a first step in research on the interaction of order pickers' writing and travel direction and, specifically, its impact on performance in the context of manual picker-to-parts order-picking. Future research could consider whether our findings extend beyond the setting studied here—order pickers traveling on industrial trucks—to settings in which pickers are required to walk, considering that travel speed could influence the decision-making process; higher speeds on industrial trucks may necessitate more rapid decision-making, and the slow speed of walking may afford pickers more time to orient themselves, suggesting an identical underlying mechanism but with varying decision-making velocities.

Further research approaches could examine the same interaction effect on an alternative but relevant dependent variable, namely the quality of completed tasks, a variable not observed in the current study due to an error rate of $\sim 0.05\%$ resulting in insufficient data. Our observations in the warehouse suggest that writing direction could also be relevant to the selection of the correct item in search tasks (Batt and Gallino, 2019), for example, in high-density storage systems.

Future studies can build on our findings concerning the impact on performance of the interaction of order-picker writing direction and travel direction by studying how other DEI-related factors interact with operational design policies (Corbett, 2023). Lastly, considering the recent increase in the use of robotic coworkers, future studies could investigate how the role of DEI in OM may be impacted by these technologies and their design—for example, human-leading robot-following versus robot-leading human-following schemes.

Appendix 1. Descriptive Statistics and Cross-Correlation

	Min.	Mean	Max.	SD	VIF	1	2	3	4	5	6	7	8
1: Travel_Pick_Time	3.00	19.60	60.00	12.01									
2: Left_To_Right_ Writing	0.00	0.56	1.00	0.49	1.00	0.01***							
3: Travel_Direction	1.00	1.99	3.00	0.83	1.37	0.02***	0.00***						
4: Travel_Distance	0.60	17.21	149.40	26.50	1.02	0.13***	0.01***	−0.02***					
5: Product_Weight	0.03	3.15	24.98	3.06	1.28	0.06***	0.04***	0.00	0.02***				
6: Product_Volume	0.05	10.64	25	5.36	1.08	0.07***	0.07***	0.03***	0.00**	0.24***			
7: Storage_Level	0	0.26	6.60	0.65	1.01	0.00	0.00**	0.01***	−0.02***	−0.15***	−0.11***		
8: Stack_Level	1.00	62.00	111.00	5.74	1.01	0.00***	0.08***	0.00***	−0.10***	−0.15***	0.00	0.19***	
9: Pick_Density	1.00	10.64	29.00.	5.81	1.06	0.08***	0.00***	0.00***	−0.02***	0.12***	0.12***	0.01***	0.06***

VIF: variance inflation factors; SD: standard deviation.

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References

Antonakis J, Bastardoz N and Rönkkö M (2021) On ignoring the random effects assumption in multilevel models: Review, critique, and recommendations. *Organizational Research Methods* 24(2): 443–483.

Baayen RH, Davidson DJ and Bates DM (2008) Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language* 59(4): 390–412.

Bächtold D, Baumüller M and Brugger P (1998) Stimulus response compatibility in representational space. *Neuropsychologia* 36(8): 731–735.

Batt RJ and Gallino S (2019) Finding a needle in a haystack: The effects of searching and learning on pick-worker performance. *Management Science* 65(6): 2624–2645.

Bell A, Fairbrother M and Jones K (2019) Fixed and random effects models: Making an informed choice. *Quality & Quantity* 53(2): 1051–1074.

Bender A, Rothe-Wulf A and Beller S (2018) Variability in the alignment of number and space across languages and tasks. *Frontiers in Psychology* 9: 1724.

Bendoly E, Croson R, Goncalves P, et al. (2010) Bodies of knowledge for research in behavioral operations. *Production and Operations Management* 19(4): 434–452.

Bergen BK and Chan Lau TT (2012) Writing direction affects how people map space onto time. *Frontiers in Psychology* 3: 109.

Bowman DA, Koller D and Hodges LF (1997) Travel in immersive virtual environments: An evaluation of viewpoint motion control techniques. *Proceedings of IEEE 1997 Annual International Symposium on Virtual Reality* 1: 45–52.

Bromham L, Dinnage R, Skirgård H, et al. (2022) Global predictors of language endangerment and the future of linguistic diversity. *Nature Ecology & Evolution* 6(2): 231.

Buis M (2012) Stata tip 106: With or without reference. *Stata Journal* 12(1): 162–164.

Byrne P, Becker S and Burgess N (2007) Remembering the past and imagining the future: A neural model of spatial memory and imagery. *Psychological Review* 114(2): 340–375.

Chan TT and Bergen B (2005) Writing direction influences spatial cognition. *Proceedings of the Annual Meeting of the Cognitive Science Society* 27: 412–417.

Collins AM and Loftus EF (1975) A spreading-activation theory of semantic processing. *Psychological Review* 82(6): 407–428.

Corbett CJ (2024) OM Forum—The operations of well-being: An operational take on happiness, equity, and sustainability. *Manufacturing & Service Operations Management* 26(2): 409–430.

Darken RP and Peterson B (2014) Spatial orientation, wayfinding, and representation. In Hale KS and Stanney KM (eds), *Handbook of Virtual Environments*. CRC Press.

Dehaene S, Bossini S and Giraux P (1993) The mental representation of parity and number magnitude. *Journal of Experimental Psychology: General* 122(3): 371–396.

de Vries J, de Koster RBM and Stam D (2016a) Aligning order picking methods, incentive systems, and regulatory focus to increase performance. *Production and Operations Management* 25(8): 1363–1376.

de Vries J, de Koster RBM and Stam D (2016b) Exploring the role of picker personality in predicting picking performance with pick by voice, pick to light and RF-terminal picking. *International Journal of Production Research* 54(8): 2260–2274.

Dobel C, Diesendruck G and Bölte J (2007) How writing system and age influence spatial representations of actions: A developmental, cross-linguistic study. *Psychological Science* 18(6): 487–491.

Donohue K, Özer Ö and Zheng Y (2020) Behavioral operations: Past, present, and future. *Manufacturing & Service Operations Management* 22(1): 191–202.

Evans GW, Skorpanich MA, Gärling T, et al. (1984) The effects of pathway configuration, landmarks and stress on environmental cognition. *Journal of Environmental Psychology* 4(4): 323–335.

Faghihi N, Garcia O and Vaid J (2019) Spatial bias in figure placement in representational drawing: Associations with handedness and script directionality. *Laterality* 24(5): 614–630.

Finnsgård C, Wänströ C, Medbo L, et al. (2011) Impact of materials exposure on assembly workstation performance. *International Journal of Production Research* 49(24): 7253–7274.

Finnsgård C and Wänström C (2013) Factors impacting manual picking on assembly lines: An experiment in the automotive industry. *International Journal of Production Research* 51(6): 1789–1798.

Fitch WT (2010) *The Evolution of Language*. 1. publ ed. Cambridge: Cambridge University Press.

Gärdenfors P (2020) Primary cognitive categories are determined by their invariances. *Frontiers in Psychology* 11: 584017.

Gärling T, Böök A and Lindberg E (1986a) Spatial orientation and wayfinding in the designed environment: A conceptual analysis and some suggestions for postoccupancy evaluation. *Journal of Architectural and Planning Research* 3(1): 55–64.

Gärling T, Lindberg E, Carreiras M, et al. (1986b) Reference systems in cognitive maps. *Journal of Environmental Psychology* 6(1): 1–18.

Gevers W, Reynvoet B and Fias W (2003) The mental representation of ordinal sequences is spatially organized. *Cognition* 87(3): B87–B95.

Grosse EH and Glock CH (2015) The effect of worker learning on manual order picking processes. *International Journal of Production Economics* 170: 882–890.

Hanson R and Finnsgård C (2014) Impact of unit load size on in-plant materials supply efficiency. *International Journal of Production Economics* 147: 46–52.

Hanson R, Medbo L and Johansson MI (2018) Performance characteristics of robotic mobile fulfilment systems in order picking applications. *IFAC-PapersOnLine* 51(11): 1493–1498.

Huttenlocher J (1968) Constructing spatial images: A strategy in reasoning. *Psychological Review* 75(6): 550–560.

Jul S and Furnas GW (1997) Navigation in electronic worlds. *ACM SIGCHI Bulletin* 29(4): 44–49.

Kazandjian S, Dupierrix E, Gaash E, et al. (2009) Egocentric reference in bidirectional readers as measured by the straight-ahead pointing task. *Brain Research* 1247: 133–141.

Kinsbourne M (1987) Mechanisms of unilateral neglect. *Advances in Psychology* 45: 69–86.

Lopiccolo D and Chang CB (2021) Cultural factors weaken but do not reverse left-to-right spatial biases in numerosity processing: Data from Arabic and English monoliterates and Arabic-English biliterates. *PloS one* 16(12): e0261146.

Loske D (2022) Empirical evidence on human learning and work characteristics in the transition to automated order picking. *Journal of Business Logistics* 43(3): 302–342.

Maass A, Pagani D and Berta E (2007) How beautiful is the goal and how violent is the fistfight? Spatial bias in the interpretation of human behavior. *Social Cognition* 25(6): 833–852.

Maass A, Suitner C and Deconchy J-P (2016) *Living in an Asymmetrical World: How Writing Direction Affects Thought and Action*. A Psychology Press Book. London and New York: Routledge.

Masae M, Glock CH and Grosse EH (2020) Order picker routing in warehouses: A systematic literature review. *International Journal of Production Economics* 224: 107564.

Masson N, Andres M, Alsamour M, et al. (2020) Spatial biases in mental arithmetic are independent of reading/writing habits: Evidence from French and Arabic speakers. *Cognition* 200: 104262.

Matusiak M, de Koster RBM and Saarinen J (2017) Utilizing individual picker skills to improve order batching in a warehouse. *European Journal of Operational Research* 263(3): 888–899.

Mishra H, Mishra A and Moreno O (2015) Bias in spatial risk assessment. *Management Science* 61(4): 851–863.

Ninaus M, Moeller K, Kaufmann L, et al. (2017) Cognitive mechanisms underlying directional and non-directional spatial-numerical associations across the lifespan. *Frontiers in Psychology* 8: 1421.

Pan JC-H, Wu M-H and Chang W-L (2014) A travel time estimation model for a high-level picker-to-part system with class-based storage policies. *European Journal of Operational Research* 237(3): 1054–1066.

Petersen CG, Siu C and Heiser DR (2005) Improving order picking performance utilizing slotting and golden zone storage. *International Journal of Operations & Production Management* 25(10): 997–1012.

Román A, El Fathi A and Santiago J (2013) Spatial biases in understanding descriptions of static scenes: The role of reading and writing direction. *Memory & Cognition* 41(4): 588–599.

Rosch EH (1973) Natural categories. *Cognitive Psychology* 4(3): 328–350.

Santoro I, Sors F, Mingolo S, et al. (2021) The influence of encoding and testing directions on retrieval of spatial information in explored and described environments. *The Journal of General Psychology* 148(1): 2–25.

Shaki S, Fischer MH and Petrusic WM (2009) Reading habits for both words and numbers contribute to the snarc effect. *Psychonomic Bulletin and Review* 16(2): 328–331.

Suchman LA (1987) *Plans and Situated Actions: The Problem of Human-machine Communication*. Plans and situated actions: The problem of human-machine communication. New York, NY, US: Cambridge University Press.

Suitner C and Giacomantonio M (2012) Seeing the forest from left to right. *Social Psychological and Personality Science* 3(2): 180–185.

Sun J, Zhang DJ, Hu H, et al. (2022) Predicting human discretion to adjust algorithmic prescription: A large-scale field experiment in warehouse operations. *Management Science* 68(2): 846–865.

Taylor HG and Heilman KM (1980) Left-hemisphere motor dominance in righthanders. *Cortex; A Journal Devoted to the Study of the Nervous System and Behavior* 16(4): 587–603.

Tversky B, Kugelmass S and Winter A (1991) Cross-cultural and developmental trends in graphic productions. *Cognitive Psychology* 23(4): 515–557.

von Hecker U and Klauer KC (2021) Are rank orders mentally represented by spatial arrays? *Frontiers in Psychology* 12: 613186.

Wänström C and Medbo L (2008) The impact of materials feeding design on assembly process performance. *Journal of Manufacturing Technology Management* 20(1): 30–51.

Wooldridge JM (2020) *Introductory Econometrics: A Modern Approach*. Seventh ed. Boston, MA: Cengage.

Zebian S (2005) Linkages between number concepts, spatial thinking, and directionality of writing: The snarc effect and the reverse snarc effect in English and Arabic monoliterates, biliterates, and illiterate Arabic speakers. *Journal of Cognition and Culture* 5(1-2): 165–190.

Zhou D, Zhong H, Dong W, et al. (2019) The metaphoric nature of the ordinal position effect. *Quarterly Journal of Experimental Psychology* 72(8): 2121–2129.

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